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A TIME SERIES AND INTERVENTION ANALYSIS OF MILLIMETER WAVE (MMW) RADIOMETRIC DATA

Richard T. Maruyama

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US ARMY ARMAMENT RESEARCH AND DEVELOPMENT COMMAND
BALLISTIC RESEARCH LABORATORY
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20. ABSTRACT (Continue on reverse side if necessary and identify by block number) (eal)

A series of tests were conducted in August 1978 to collect radiometric (electromagnetic radiation) data at the North East Test Site of the Rome Air Development Center in Rome, N.Y. This radiometric data was collected using a millimeter wave (MMW) sensoring system. Both background (ground noise) and target data were collected to investigate the signal characteristics of the sensor system. The data was recorded at equally spaced time intervals over five ranges. The purpose of the sensor is to detect and then aim at the target. (Continued)

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Item 20. Abstract (Continued)

The Box and Jenkins time series technique was used in an effort to model the background and target radiometric data. This effort resulted in an Autoregressive Integrated Moving Average (ARIMA) model of order p=1, d=0, and q=1, where the autoregressive parameter ranged from 0.73 to 0.88 and the moving average parameter ranged from -0.59 to -0.64. This ARIMA(1,0,1) model gave surprisingly good results in characterizing the background noise of the millimeter wave sensor system.

TABLE OF CONTENTS

LIST OF ILLUSTRATIONS

LIST OF TABLES

I. INTRODUCTION

An antiarmor munition is being developed and tested by the US Army Armament Research and Development Command (ARRADCOM). The lead laboratory for the program is ARRADCOM's Large Caliber Weapon System Laboratory (LCWSL). The system's analysis and sensor technology research is ongoing at the Ballistic Research Laboratory (BRL), Aberdeen Proving Ground, MD. As part of this BRL effort the millimeter wave (MMW) radiometric sensor was tested in August 1978 at the North East Test Site of the Rome Air Development Center in Rome, NY. This electromagnetic radiation data collected in Rome, NY, is related to the absolute temperature of the ground surface at the sensor's focus point, and is referred to as radiance η. The functional relationship between absolute temperature and the radiance is given in equation (1):

$$\eta = 2kT/\lambda^2 \tag{1}$$

where k is Boltzmann's constant

T is the absolute temperature

and λ is the wavelength.

The radiometric data were collected over field and wooded areas, at five different slant ranges from 30 to 150 meters (see Figure 1). The MMW sensor was mounted on a helicopter at a squint angle of 30°, measured from perpendicular to the ground. The helicopter was then flown at a ground speed of 60 knots. The MMW sensor had a spin rate of 4 revolutions per second and recorded data continuously. Then, the data was digitized by sampling approximately two thousand equally spaced observations per second.

Representative plots of the August 1978 MMW data are presented in Figure 2 and Figure 3. Figure 2 is a typical terrain (non-target) response, whereas Figure 3 is a response with a target. The absolute temperature T in Equation (1) has been adjusted in Figure 2 and Figure 3 by subtracting the average ground temperature plus an arbitrary offset. Hereafter, the symbol T will be referred to as the contrast temperature. The analysis of the system's response to a target (Figure 3) will be discussed in Section IV.

The purpose of the sensor is to detect the target and then aim the weapon system under battlefield conditions. Hence, the response of the MMW sensor to varying background conditions will affect the weapon system's ability to detect targets.

The radiometric non-target and target observations were modeled using the Box and Jenkins approach. The analysis demonstrates the ability of the ARIMA model to characterize the radiometric data.

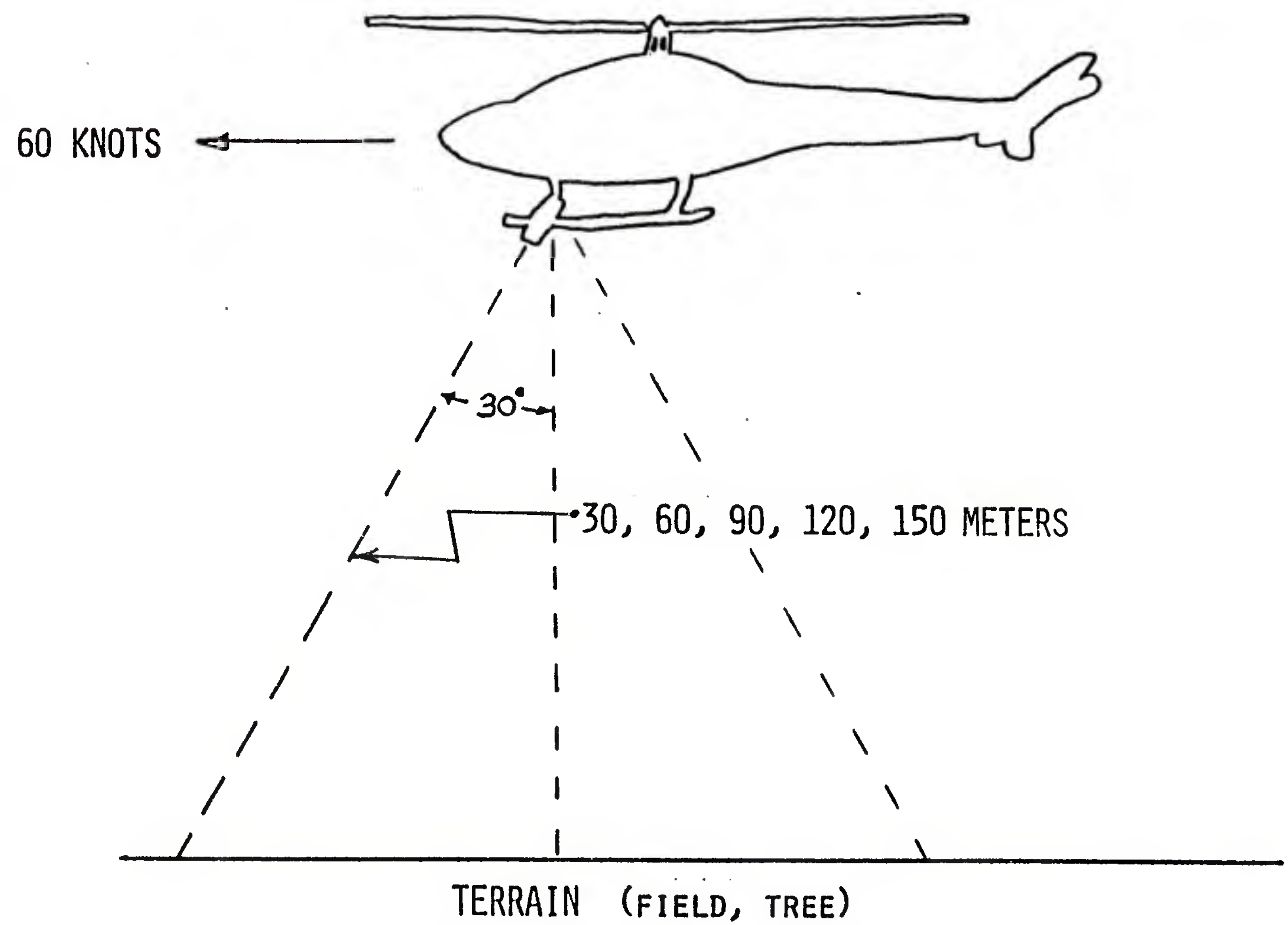
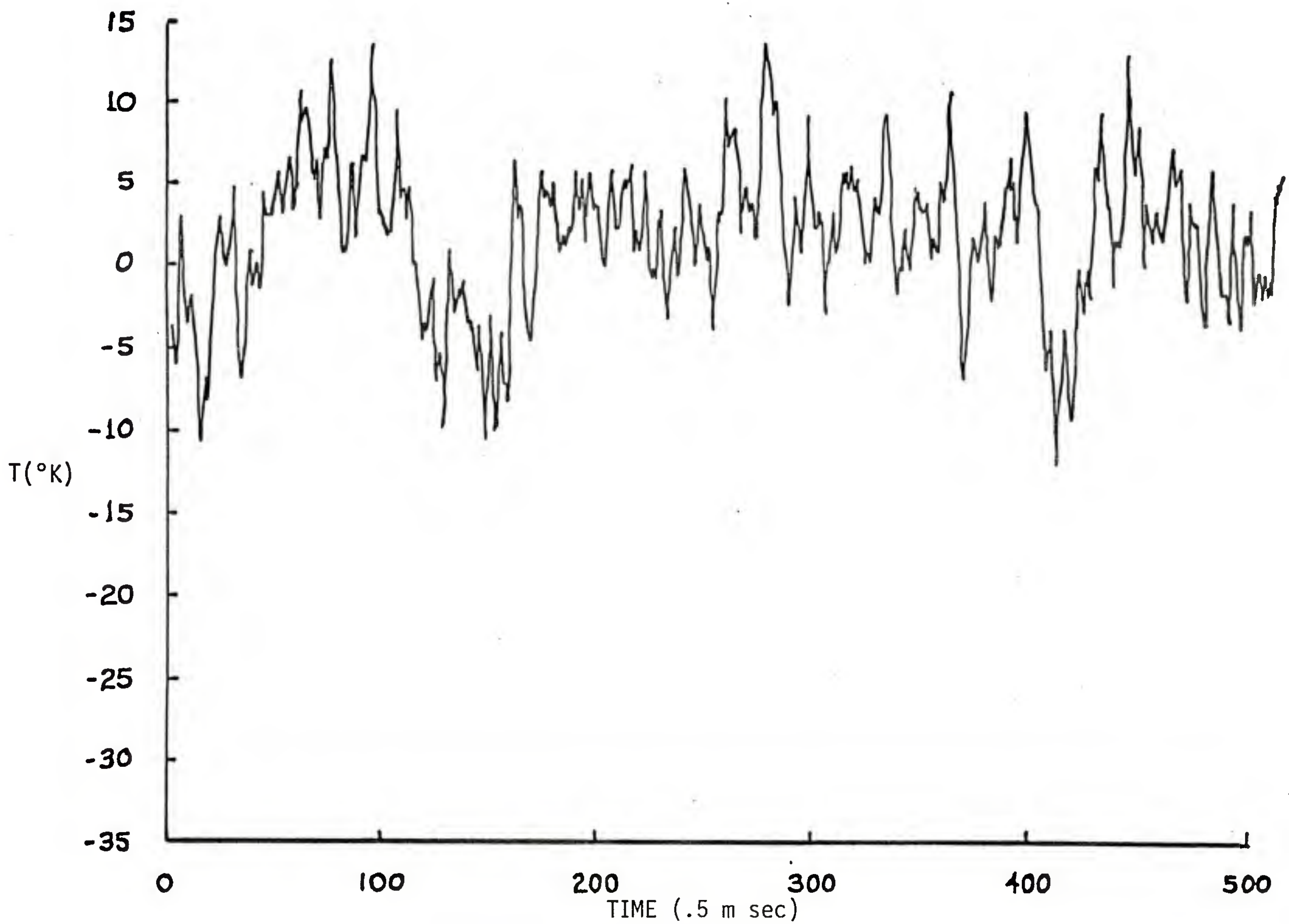
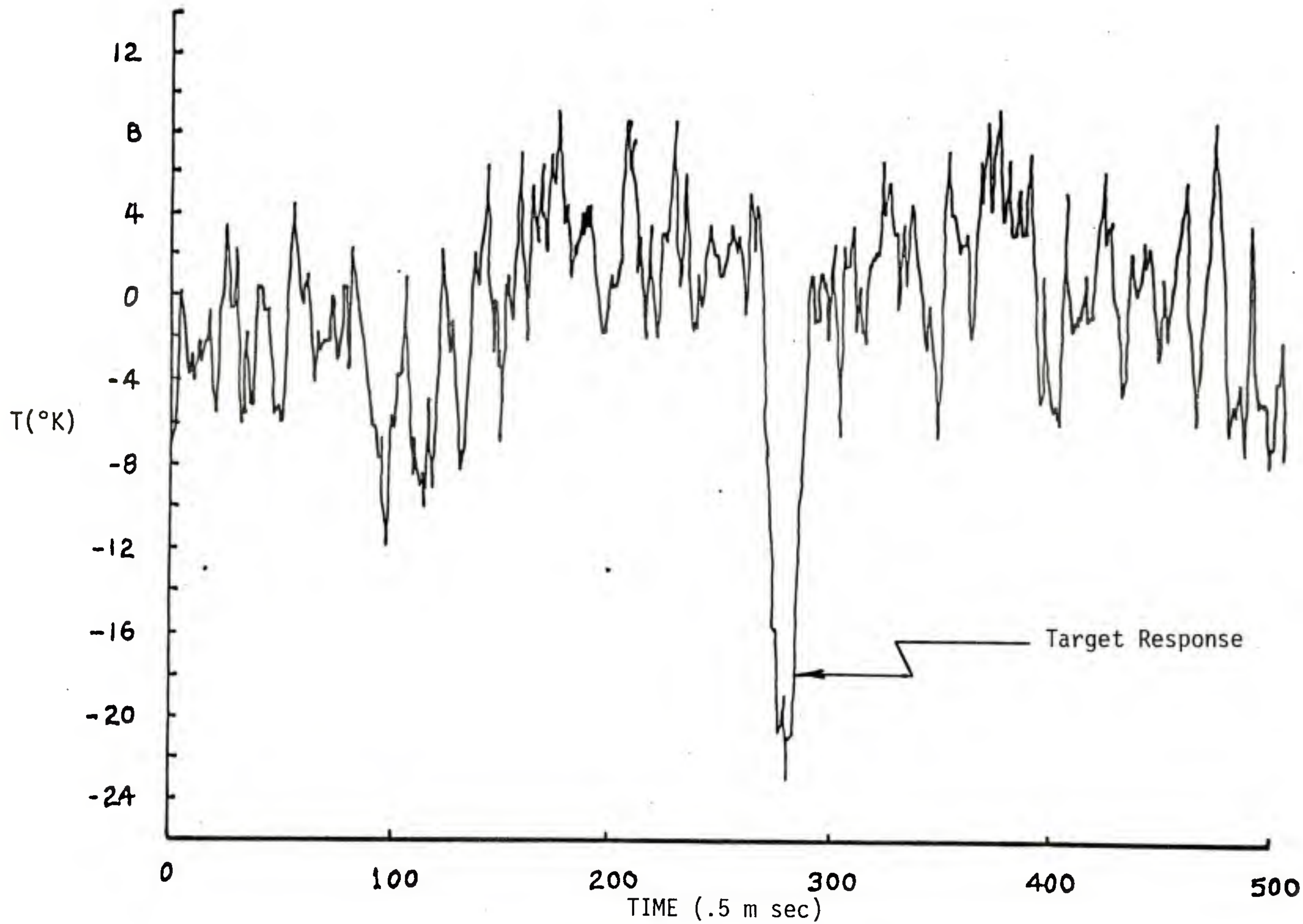


FIGURE 1. NORTH EAST TEST SITE OF THE ROME AIR DEVELOPMENT CENTER IN ROME, N.Y. AUGUST 1978



CONTRAST TEMP vs. TIME

Figure 2. MMW Data (No Target).



CONTRAST TEMP vs. TIME

Figure 3. MMW Data (Target).

II. THE BOX AND JENKINS TIME SERIES APPROACH

The Box and Jenkins[1] Autoregressive Integrated Moving Average (ARIMA (p,d,q)) model is used to characterize many types of business, economics and engineering observations. A requirement to develop a model of the MMW sensors' responses to backgrounds (terrain) has existed at BRL for some time. A new approach using the Box and Jenkins time series methodology was used to model the sensors' responses.

The ARIMA (p,d,q) model is presented below:

$$\phi_p(B)(1-B)^d(Z_t-\mu) = \theta_q(B)a_t \tag{2}$$

where B is the backshift operator such that $BZ_t = Z_{t-1}$,

$\phi_p(B)$ is a polynomial in B of order p and ϕ_i are autoregressive parameters,

$\theta_q(B)$ is a polynomial in B of order q and θ_i are moving average parameters,

p,d,q are non-negative integers, and refer to the order of the respective autoregressive operators, the d^{th} difference and the moving average operator,

a_t are random shocks (white noise) assumed to be independently distributed normal variates, $N(0,\sigma_a^2)$ at time t, and in this application Z_t are values of contrast temperature at the t^{th} time step.

A series of five hundred observations were analyzed and used to estimate the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) out to 40 lags or time steps (see Table 1 and Figure 4). The estimated mean $(\hat{\mu})$ and standard deviation $(\hat{\sigma})$ of this 500 sample time series are -1.603 and 3.712, respectively.

In building a dynamic time series model, three steps are required; (1) tentatively identify the model, (2) fit the data to the model, and (3) perform a diagnostic check for lack of fit. The identification step requires an overall view of the data structure. In this case a damping sinusoidal structure for the ACF and two significant spikes at the first and second PACF (see Figure 4) implies that an autoregressive model of order p=2 be initially entertained. Hence, the ARIMA (2,0,0) model was fitted.

ARIMA (2,0,0) Initially Entertained

$$(1 - \phi_1 B - \phi_2 B^2)(Z_t - \mu) = a_t \tag{3}$$

where the estimated parameters are

$$\hat{\mu} = -1.636$$
$$\hat{\phi}_1 = 1.252$$
$$\hat{\phi}_2 = -0.450.$$

[1] Box, E. E. P. and Jenkins, G. M., Time Series Analysis: Forecasting and Control, San Francisco, CA, Holden-Day, 1970.

TABLE 1. ESTIMATED AUTOCORRELATION AND PARTIAL AUTOCORRELATION FUNCTIONS

MMW RADIOMETRIC READING: 2000 observations per second

Autocorrelations (ACF)

500 Observations

		1	2	3	4	5	6	7	8	9	10
Z	Lags 1-10	.86	.63	.46	.35	.27	.21	.17	.15	.15	.15
	11-20	.17	.22	.27	.33	.37	.40	.39	.36	.32	.28
	21-30	.23	.17	.11	.07	.04	.04	.06	.12	.18	.23
	31-40	.26	.31	.36	.37	.31	.23	.16	.10	.04	-.03
∇Z	Lags 1-10	.34	-.21	-.22	-.11	-.08	-.07	-.08	-.06	-.02	-.06
	11-20	-.09	-.04	.02	.01	.09	.12	.06	.03	.04	.01
	21-30	.02	.01	-.03	-.10	-.06	-.11	-.11	-.02	.06	.04
	31-40	-.05	.01	.15	.22	.12	-.07	-.05	.04	-.00	-.12

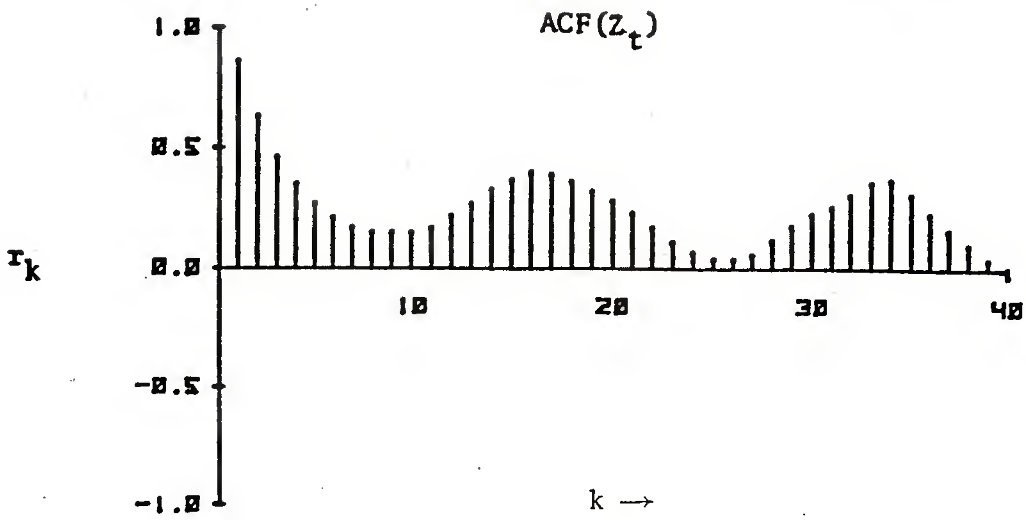
Partial Autocorrelations (PACF)

500 Observations

		1	2	3	4	5	6	7	8	9	10
Z	Lags 1-10	.86	-.43	.25	-.09	.03	.01	.02	.04	.03	.02
	11-20	.12	.09	.08	.09	.11	-.02	.03	.03	-.01	-.02
	21-30	-.00	-.06	-.03	-.03	.03	-.05	.11	.04	.02	.01
	31-40	.06	.14	.01	-.06	-.09	-.04	.06	-.10	-.06	-.04
∇Z	Lags 1-10	.34	-.37	.01	-.12	-.08	-.09	-.11	-.08	-.07	-.15
	11-20	-.12	-.10	-.11	-.12	.02	-.05	-.04	-.00	.01	-.01
	21-30	.05	.01	.02	-.05	.04	-.14	-.05	-.04	-.01	-.08
	31-40	-.14	-.01	.05	.08	.04	-.08	.10	.04	.03	-.05

$\hat{\mu}_z$ = -1.603

$\hat{\sigma}_z$ = 3.712



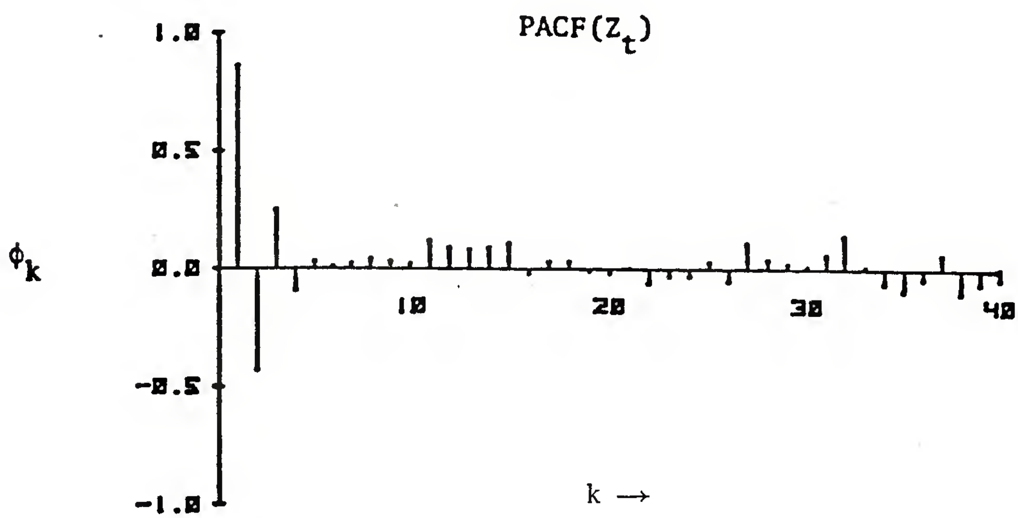


Figure 4. **Estimated Autocorrelation** (r_k) and Partial Autocorrelation Functions (ϕ_k) for the kth Lag.

The autocorrelation function of the residual, $a_t = Z_t - \hat{Z}_t$, of the ARIMA (2,0,0) model was checked for lack of fit. These residual ACF are listed in Table 2, where the estimated residual mean and standard deviation are $\hat{\mu}_{a_t} = 0.00175$ and $\hat{\sigma}_{a_t} = 1.681$. The ACF of the residuals at lags k=1 and k=2 indicated some remaining residual structure (see Figure 5). The cutoff of the residual ACF suggests a possible need for a moving average term in the model.

Hence, the ARIMA (2,0,1) model was entertained in order to remove the spikes in the residual ACF. The ARIMA (2,0,1) model is as follows:

ARIMA (2,0,1)

$$(1 - \phi_1 B - \phi_2 B^2)(Z_t - \mu) = (1 - \theta_1 B)a_t \tag{4}$$

where the estimated parameters are

$$\hat{\mu} = -1.622$$
$$\hat{\phi}_1 = 0.886$$
$$\hat{\phi}_2 = -0.138$$
$$\hat{\theta}_1 = -0.506 .$$

The addition of the moving average term, θ_1, removed the autocorrelation spikes for lags k = 1 and k = 2 (see Table 3). Inspection of the residuals with mean $\hat{\mu}_{a_t} = 0.0009$ and standard deviation $\hat{\sigma}_{a_t} = 1.616$, where the sample ACF and PACF values are small, indicates a good fit (see Figure 6). The 95% confidence interval for the second estimated autoregressive parameter, $\hat{\phi}_2 = -0.138$, overlapped the zero point (-0.285, 0.0086). This suggested the possible removal of this term from the model. Based on this information and the principle of parsimony in the use of parameters, the second autoregressive parameter, ϕ_2, was removed and the ARIMA (1,0,1) model was then considered.

The ARIMA (1,0,1) model is as follows:

ARIMA (1,0,1)

$$(1 - \phi_1 B)(z_t - \mu) = (1 - \theta_1 B)a_t \tag{5}$$

where the new estimated parameters are

$$\hat{\mu} = -1.618$$
$$\hat{\phi}_1 = 0.7553$$
$$\hat{\theta}_1 = -0.5960 .$$

TABLE 2

ESTIMATED AUTOCORRELATION AND PARTIAL AUTOCORRELATION FUNCTIONS OF RESIDUALS

(ARIMA (2,0,0))

Residual Mean = .001747

Residual Standard Deviation = 1.6809

ACF

500 Observations

		1	2	3	4	5	6	7	8	9	10
r_k	Lags 1-10	.12	-.21	.01	.10	.07	.04	.01	.01	.08	.02
	11-20	-.02	.04	.09	.01	.11	.14	.05	.04	.08	.04
	21-30	.06	.05	.04	-.05	.06	-.01	-.05	.04	.10	.08

PACF

500 Observations

		1	2	3	4	5	6	7	8	9	10
ϕ_k	Lags 1-10	.12	-.22	.07	.05	.07	.06	.02	.02	.07	-.00
	11-20	-.00	.04	.06	-.00	.14	.10	.06	.06	.07	.01
	21-30	.05	.01	.03	-.08	.05	-.09	-.04	-.02	.06	.05

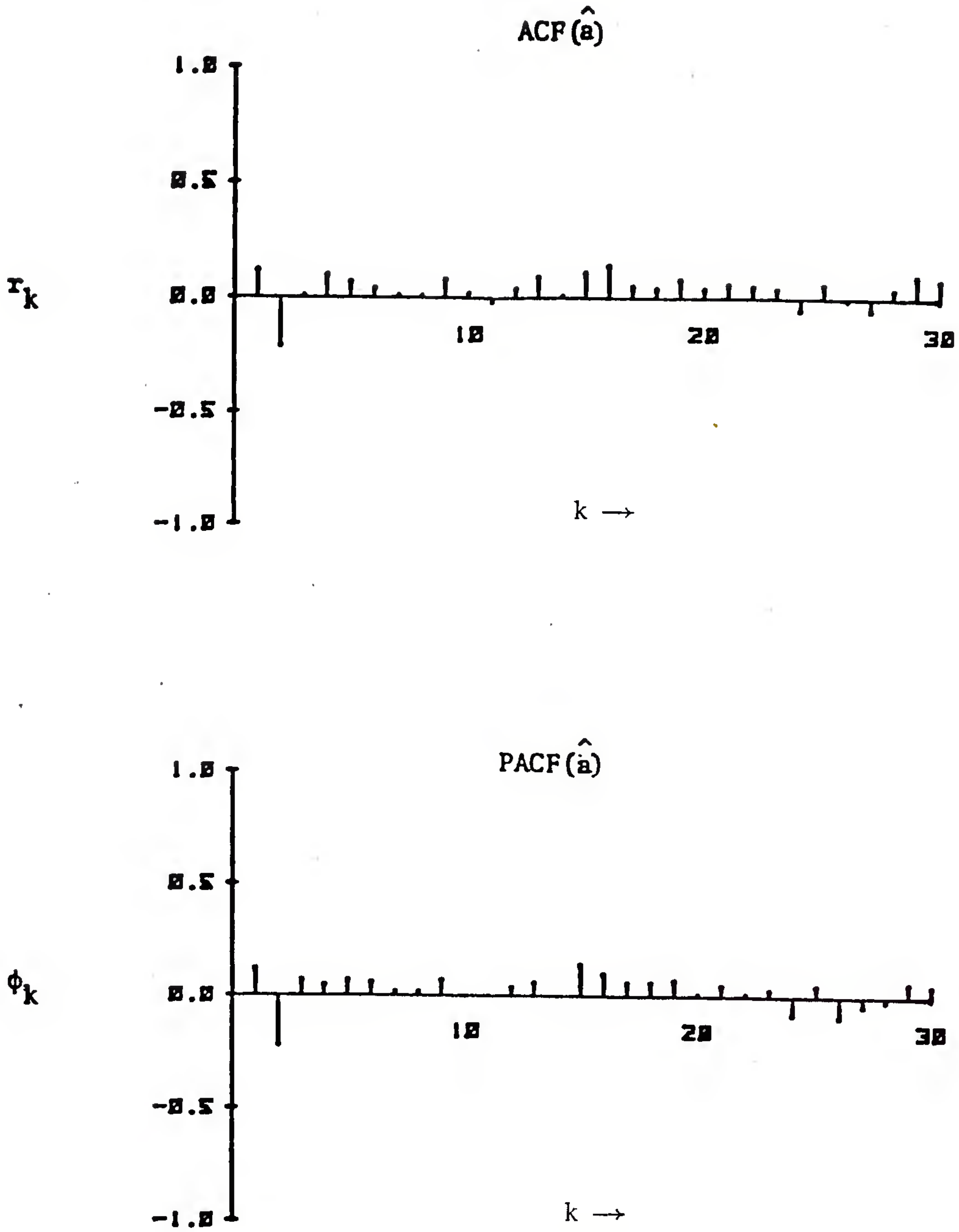


Figure 5. **Plot of the Estimated ACF** (r_k) and PACF (ϕ_k) of Residuals (ARIMA (2,0,0)) for the kth Lag.

TABLE 3

ESTIMATED AUTOCORRELATION AND PARTIAL AUTOCORRELATION FUNCTIONS OF RESIDUALS (ARIMA (2,0,1))

Residual Mean = 0.0009

Residual Standard Deviation = 1.6169

ACF

500 Observations

		1	2	3	4	5	6	7	8	9	10
r_k	Lags 1-10	.00	-.02	-.03	.05	.01	.02	-.01	-.01	.05	-.00
	11-20	-.02	.01	.09	-.00	.11	.11	.06	.04	.09	.02
	21-30	.07	.01	.05	-.09	.05	-.05	-.04	.02	.06	.07

PACF

500 Observations

		1	2	3	4	5	6	7	8	9	10
ϕ_k	Lags 1-10	.00	-.02	-.03	.05	.01	.02	-.00	-.02	.05	-.01
	11-20	-.02	.02	.08	-.00	.12	.12	.06	.05	.09	.02
	21-30	.07	.01	.06	-.09	.04	-.06	-.06	-.01	.03	.05

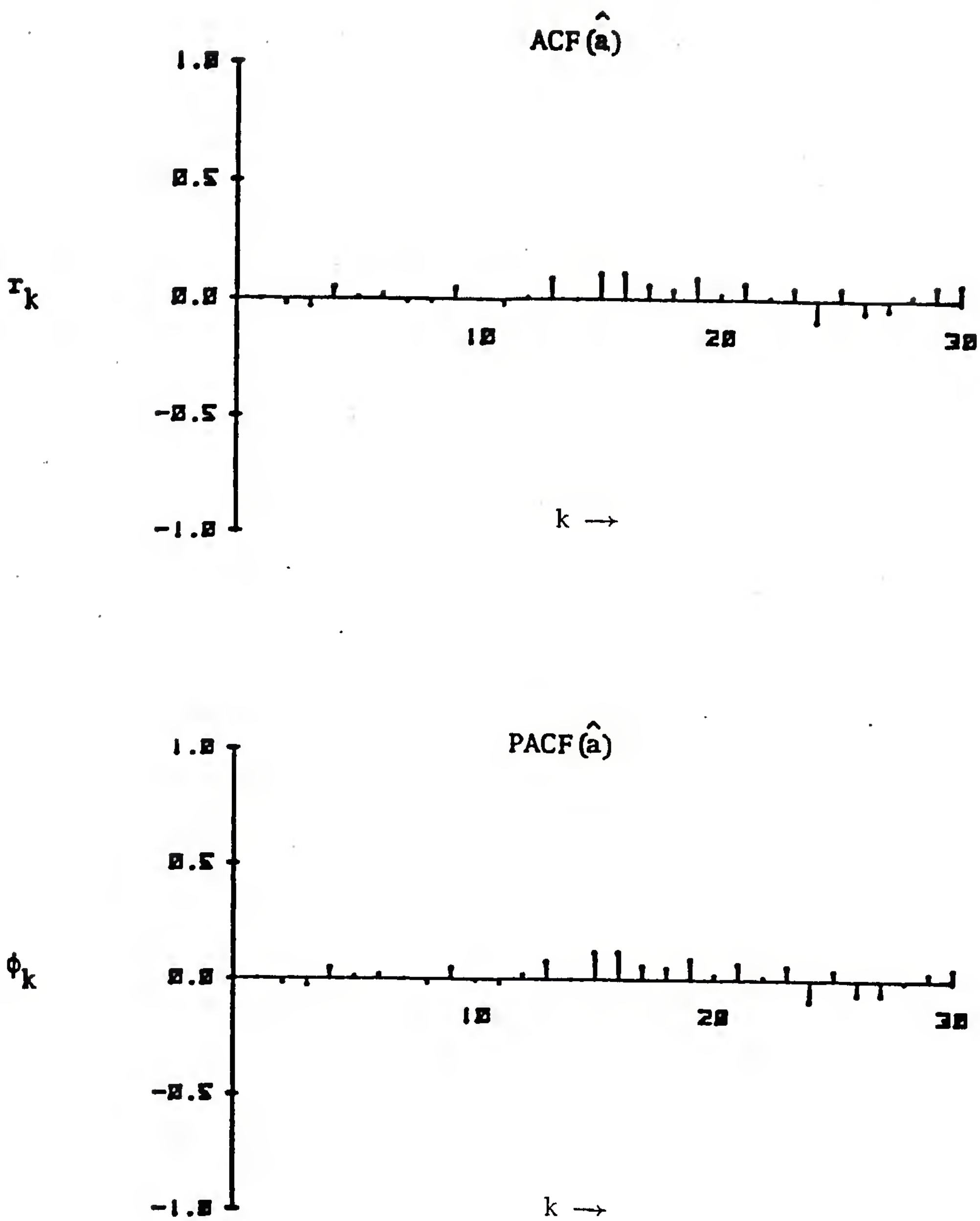


Figure 6. **Plot of the Estimated ACF** (r_k) and PACF (ϕ_k) of Residuals (ARIMA (2,0,1)) for the kth Lag.

Both the ACF and PACF of the ARIMA (1,0,1) residuals indicated an excellent fit. Table 4 and Figure 7 show that the residual, $\{a_t = z_t - \hat{z}_t\}$, contains no further structure. Additional attempts to better characterize this time series were unsuccessful.

A summary of the models and their estimated parameters is presented in Table 5.

III. APPLICATION OF THE ARIMA (1,0,1) MODEL TO ADDITIONAL NON-TARGET MMW DATA

In Section 2, the rationale for the selection of the ARIMA (1,0,1) model was presented. In this section, additional non-target cases are analyzed. The ARIMA (1,0,1) model was found to be adequate for modeling these additional sets of non-target MMW data collected in Rome, N.Y.

In Table 6, both the ACF and PACF of additional samples of 500 observations at different distances (30, 60, 90, 120 and 150 meters) were estimated. Plots of these ACF's and PACF's are presented in Figure 8. The similarity in the correlograms raised the possibility of modeling all the non-target data with the same ARIMA model. Hence, Table 7 was generated from 30 additional sets of data using the ARIMA (1,0,1) model.

This analysis suggested that the estimated means $(\hat{\mu})$ are not fixed, whereas the autoregressive parameter $(\hat{\phi}_1)$ and the moving average parameter $(\hat{\theta}_1)$ varied only slightly. The white noise estimated parameters $(\hat{\mu}_a, \hat{\sigma}_a)$ were consistently similar for those cases investigated. That is, $\hat{\mu}_a \approx 0.0$ and $\hat{\sigma}_a \approx$ (1.62 to 1.79), further suggesting the utility of this noise model approach. A closer look at the residuals, a_t, indicated a lack of any consistent pattern after fitting the ARIMA (1,0,1) model. Figure 9 shows this lack of structure in the residuals, indicating again the ability of the ARIMA (1,0,1) model to characterize the balance of the 1978 MMW non-target data. A white noise model was used to simulate the sensor's characteristics for the different cases. The ARIMA model used for this purpose is that of Equation (6).

$$z_t = (1 - \hat{\phi})\hat{\mu} + a_t - \hat{\theta}a_{t-1} + \hat{\phi}z_{t-1} \qquad (6)$$

where $a_t = N(0, \hat{\sigma}_a^2)$ and
$(\hat{\mu}, \hat{\phi}, \hat{\theta})$ are the estimated parameters.

A plot of one such simulated case is shown in Figure 10 for a comparison with the actual data plotted in Figure 2.

TABLE 4

ESTIMATED AUTOCORRELATION AND PARTIAL AUTOCORRELATION FUNCTIONS OF RESIDUALS (ARIMA (1,0,1))

Residual Mean = 0.00039

Residual Standard Deviation = 1.623

ACF

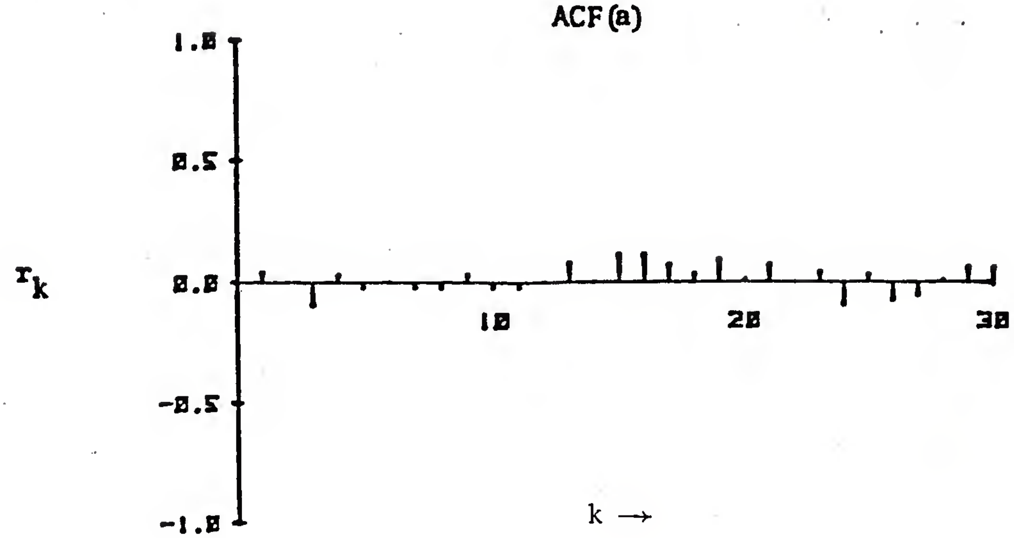
500 Observations

		1	2	3	4	5	6	7	8	9	10
r_k	Lags 1-10	.04	.00	-.09	.03	-.02	.00	-.02	-.02	.03	-.02
	11-20	-.02	.00	.08	-.00	.11	.11	.07	.03	.09	.01
	21-30	.07	.00	.04	-.09	.03	-.07	-.05	.01	.06	.06

PACF

500 Observations

		1	2	3	4	5	6	7	8	9	10
ϕ_k	Lags 1-10	.04	.00	-.09	.04	-.02	-.00	-.02	-.02	.04	-.02
	11-20	-.03	.01	.07	-.01	.12	.11	.06	.05	.10	.02
	21-30	.08	.02	.06	-.08	.04	-.06	-.06	.00	.03	.03



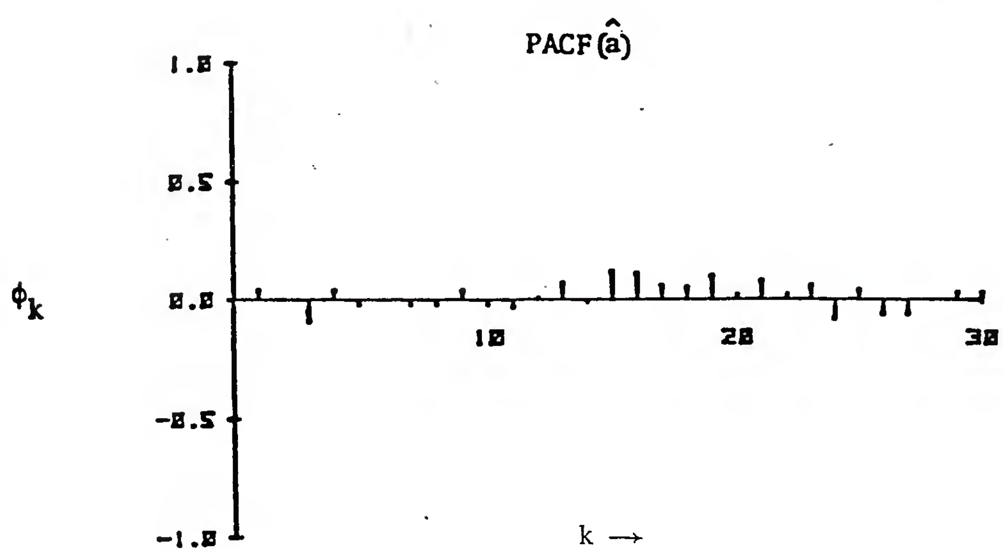


Figure 7. **Estimated ACF** (r_k) and PACF (ϕ_k) of Residuals (ARIMA (1,0,1)) for the kth Lag.

TABLE 5. A SUMMARY OF ARIMA (•) MODELS ENTERTAINED

MODEL	ESTIMATED PARAMETERS	RESIDUAL SUM SQ.	WHITE NOISE
(1) $(1-\phi_1 B-\phi_2 B^2)(Z_t-\mu) = a_t$	$\hat{\mu} = -1.636$	1,412	$\bar{a}_t = 0.0017$
	$\hat{\phi}_1 = 1.251$	497 df.	$\bar{\sigma}_a = 1.68$
	$\hat{\phi}_2 = -0.450$		
(2) $(1-\phi_1 B-\phi_2 B^2)(Z_t-\mu) =$	$\hat{\mu} = -1.622$	1,307	
$(1-\theta_1 B)a_t$	$\hat{\phi}_1 = 0.886$	496 df.	$\bar{a}_t = 0.0009$
	$\hat{\phi}_2 = -0.138$		$\bar{\sigma}_a = 1.616$
	$\hat{\theta}_1 = -0.506$		
(3) $(1-\phi_1 B)(Z_t-\mu) = (1-\theta_1 B)a_t$	$\hat{\mu} = -1.618$	1,317	
	$\hat{\phi}_1 = 0.755$	497 df.	$\bar{a}_t = 0.00039$
	$\hat{\theta}_1 = -0.596$		$\bar{\sigma}_z = 1.62$

TABLE 6

AUTOCORRELATION AND PARTIAL AUTOCORRELATION FUNCTIONS OF Z_t

ACF

500 Observations

		1	2	3	4	5	6	7	8	9	10
Z_t	Lags 1-10	.86	.63	.46	.35	.27	.21	.17	.15	.15	.15
(150 m)	11-20	.17	.22	.27	.33	.37	.40	.39	.39	.36	.32
Z_t	Lags 1-10	.86	.64	.48	.40	.35.	.30	.24	.19	.18	.21
(120 m)	11-20	.27	.32	.35	.37	.41	.47	.50	.47	.42	.36
Z_t	Lags 1-10	.85	.60	.44	.35	.28	.20	.15	.13	.14	.18
(90 m)	11-20	.21	.25	.32	.41	.48	.53	.52	.46	.38	.30
Z_t	Lags 1-10	.87	.66	.50	.39	.31	.24	.15	.09	.06	.07
(60 m)	11-20	.13	.22	.28	.32	.33	.33	.30	.26	.20	.16
Z_t	Lags 1-10	.86	.64	.50	.42	.35	.27	.21	.17	.16	.17
(30 m)	11-20	.21	.26	.29	.33	.39	.43	.44	.41	.35	.28

PACF

		1	2	3	4	5	6	7	8	9	10
Z_t (150 m)	Lags 1-10	.86	-.43	.25	-.09	.03	.01	.02	.04	.03	.02
Z_t (120 m)	Lags 1-10	.86	-.41	.26	-.01	.05	-.05	-.01	.00	.13	.09
Z_t (90 m)	Lags 1-10	.85	-.43	.32	-.10	-.01	-.04	.07	.02	.09	.06
Z_t (60 m)	Lags 1-10	.87	-.38	.20	-.06	.05	-.11	-.02	.00	.07	.09
Z_t (30 m)	Lags 1-10	.86	-.38	.33	-.13	.02	-.04	.04	-.01	.09	.08

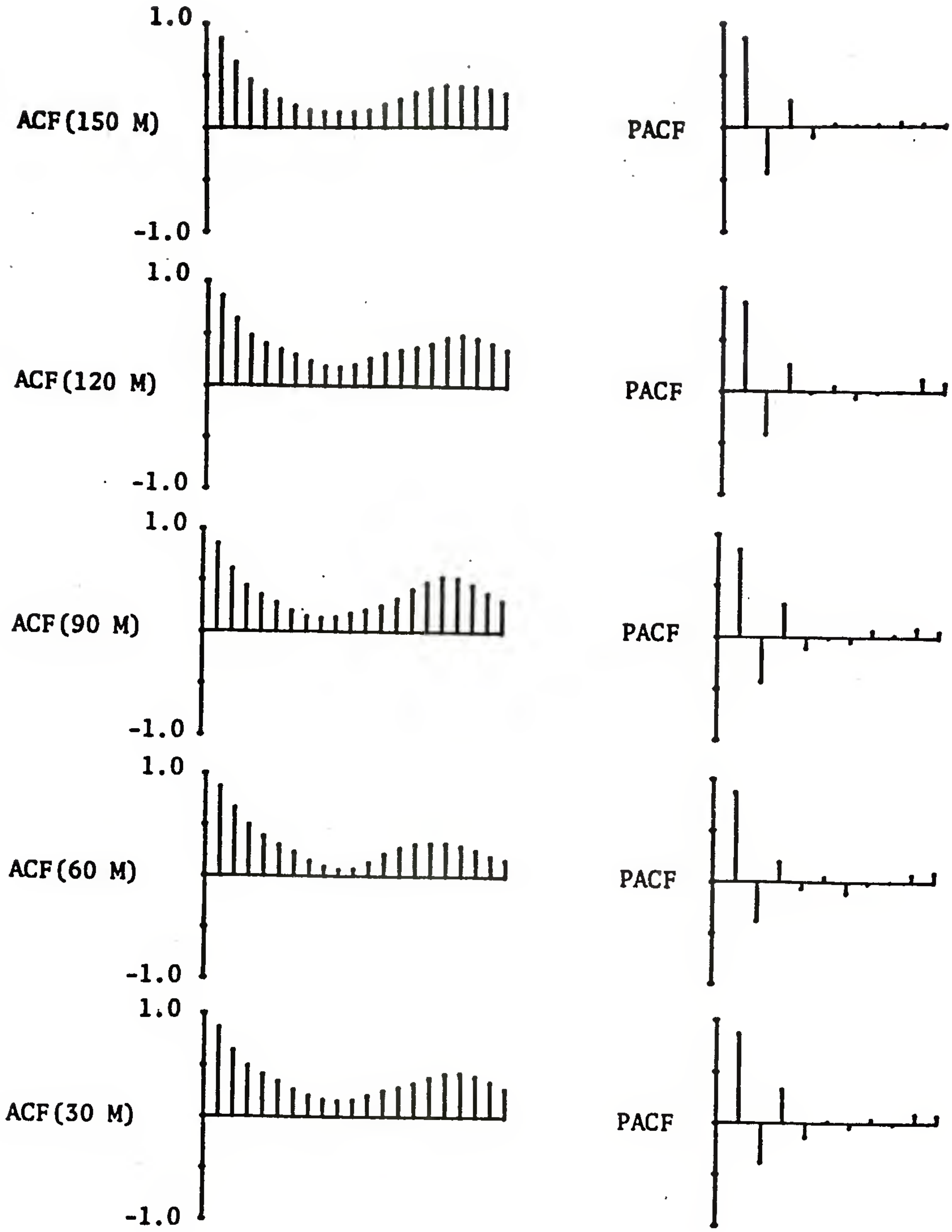


Figure 8. The ACF and PACF of (Z_t)

TABLE 7

A SUMMARY OF ADDITIONAL MMW DATA FITTED TO THE ARIMA (1,0,1) MODEL

August 2, 1978 (Field) ARIMA (1,0,1) $(1-\phi_1 B)(Z_t-\mu_z) = (1-\theta_1 B)a_t$

		$\hat{\mu}_z$	$\hat{\phi}_1$	$\hat{\theta}_1$	$\hat{\mu}_a$	$\hat{\sigma}_a$	$\chi^2_{a(27)}$
30 Meters	(a)	-20.43	.7329	-.67395	-.00078	1.6542	49.21
	(b)	-24.12	.96376*	-.55912	-.000895	1.6323	56.06
60 Meters	(a)	-17.185	.76154	-.54864	-.000674	1.5790	58.89
	(b)	-17.456	.79747	-.60273	-.000316	1.6816	47.83
90 Meters	(a)	- 7.5447	.72707	-.63197	.000253	1.6216	65.50
	(b)	- 9.2541	.68369	-.67054	-.0003039	1.6275	56.78
120 Meters	(a)	- 7.514	.75301	-.56238	.0001229	1.5556	70.70
	(b)	- 7.909	.7572	-.57466	-.0000809	1.5959	54.47
150 Meters	(a)	- 1.618	.7552	-.5959	.000399	1.6231	45.80
	(b)	- 1.7179	.68908	-.61738	.000671	1.6515	42.67
	(c)	- 0.8284	.66975	-.67832	.0001374	1.5796	74.36
	Mean	N/A	.732691	-.610632	-.0001333	1.618355	-
	St. Dev.	N/A	.040613	.047867	.000507	0.037667	-
	*		(.753697) (.079614)				

August 4, 1978 (Field) ARIMA (1,0,1)

		$\hat{\mu}_z$	$\hat{\phi}_1$	$\hat{\theta}_1$	$\hat{\mu}_a$	$\hat{\sigma}_a$	$\chi^2_{a(27)}$
30 Meters	(a)	- 9.3985	.89142	-.57673	-.0002821	1.7345	42.50
	(b)	- 7.8494	.79993	-.61042	-.0000485	1.7487	32.29
60 Meters	(a)	6.8121	.87228	-.56256	-.0005989	1.7910	45.25
	(b)	8.4699	.80589	-.66890	.0002418	1.8386	47.28
90 Meters	(a)	23.055	.88165	-.62222	-.0000369	1.8039	55.20
	(b)	23.037	.86254	-.56396	.00031859	1.7622	51.01
120 Meters	(a)	1.2813	.91947	-.53543	.0003456	1.7566	55.01
	(b)	1.4580	.92505	-.62257	.0000953	1.7982	38.34
150 Meters	(a)	-14.029	.83538	-.67237	-.000327	1.7767	39.40
	(b)	-14.726	.87666	-.62128	-.0004968	1.9116	55.95
	Mean	N/A	.867027	-.605644	-.00007889	1.7922	-
	St. Dev.	N/A	.042567	.045512	.00033697	0.051868	-

August 4, 1978 (Trees) ARIMA (1,0,1)

		$\hat{\mu}_z$	$\hat{\phi}_1$	$\hat{\theta}_1$	$\hat{\mu}_a$	$\hat{\sigma}_a$	$\chi^2_{a(27)}$
30 Meters	(a)	- 1.2039	.73473	-.63485	-.0001325	1.6602	69.56
	(b)	- 1.4959	.81564	-.59693	-.0000552	1.747	47.10
60 Meters	(a)	- 2.6053	.82087	-.59368	-.0004588	1.7232	37.90
	(b)	- 2.0881	.75270	-.63814	-.0001127	1.7423	58.36
90 Meters	(a)	16.155	.72748	-.68935	.0002787	1.7499	42.76
	(b)	15.704	.83907	-.63629	-.0004865	1.8845	74.76
120 Meters	(a)	- 7.6494	.78241	-.62126	.0001219	1.8704	45.77
	(b)	- 7.2249	.81785	-.62218	.000946	1.8263	70.69
150 Meters	(a)	8.5403	.85605	-.59373	-.0002017	1.8195	53.10
	(b)	9.0061	.79945	-.61361	-.001264	1.8421	77.85
	Mean	N/A	.794625	-.624002	-.000136	1.78654	-
	St. Dev.	N/A	.044026	.028726	.00057	0.07243	-

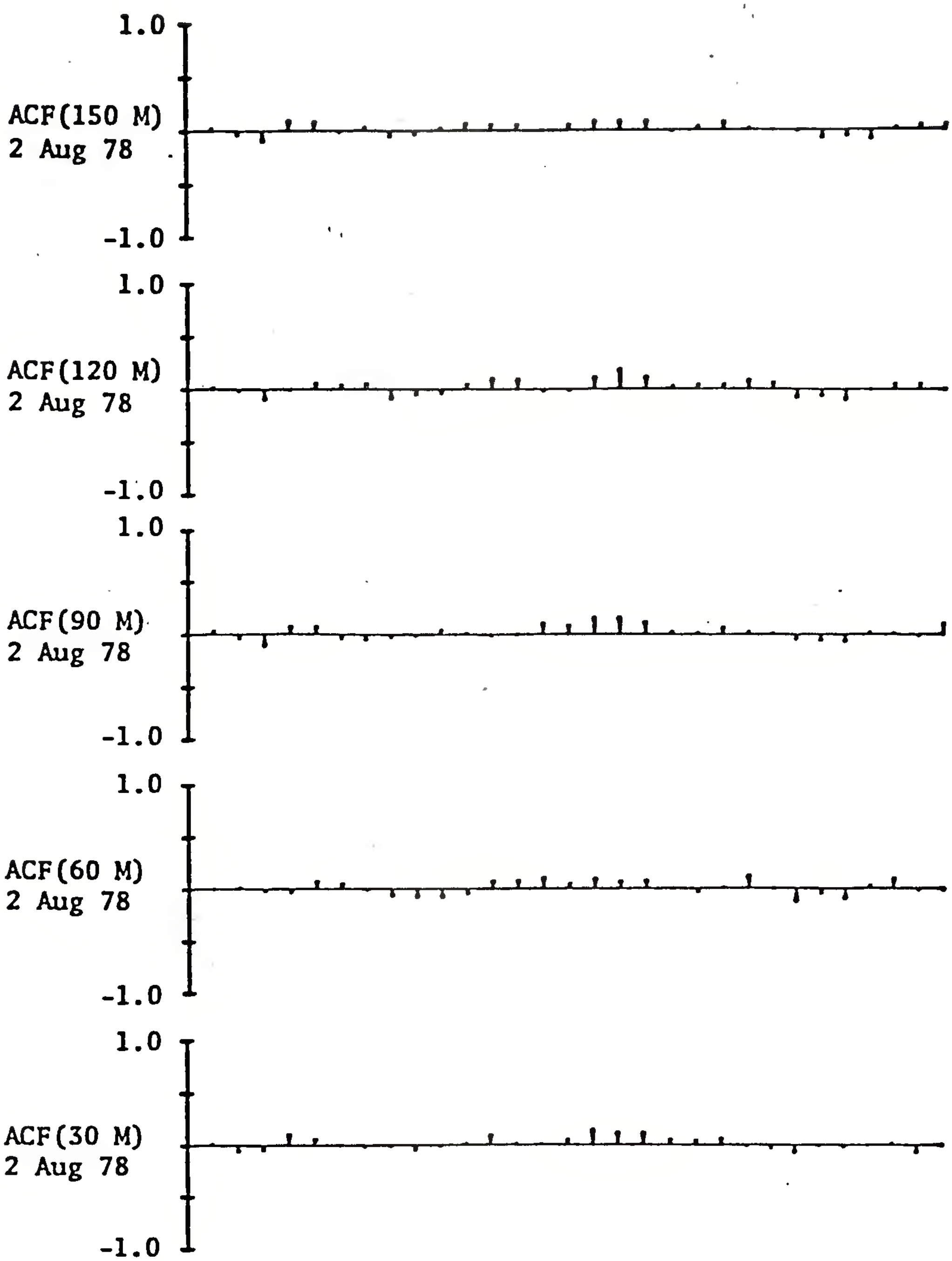
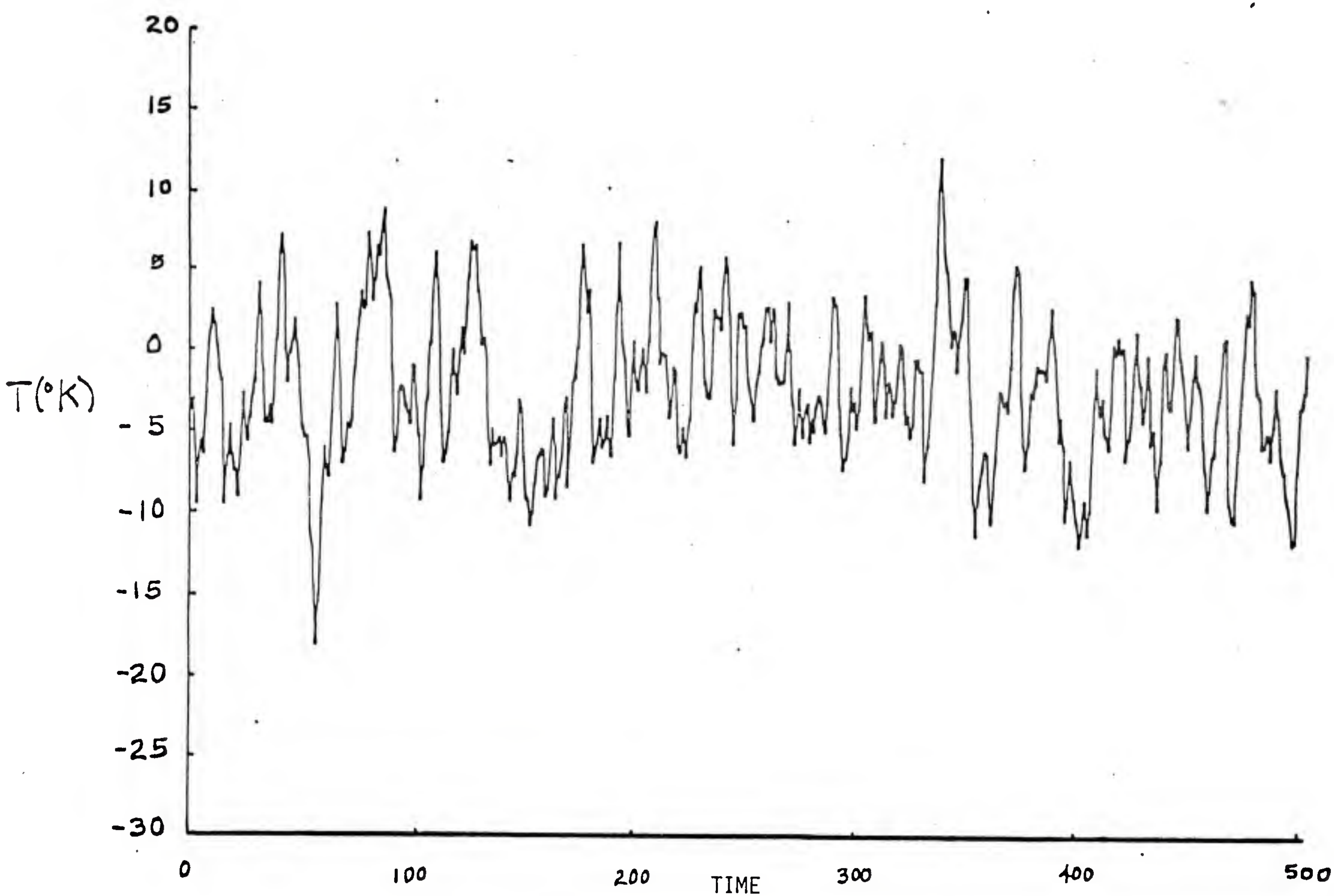


Figure 9. The Autocorrelation Function of ARIMA (1,0,1) Residuals



CONTRAST TEMP vs. TIME

Figure 10. Modeled MMW Time Series

In summary, the MMW non-target data collected in August 1978 was analyzed using the Box and Jenkins Time Series approach. This analysis indicated an ARIMA (1,0,1) model. This particular ARIMA model characterizes the data remarkably well. What is more remarkable is the consistent behavior of both the estimated parameters ($\hat{\phi}_1$, $\hat{\theta}_1$) and the white noise parameters ($\hat{\mu}_a$, $\hat{\sigma}_a$). It is recommended that the ARIMA (1,0,1) model be used to describe the non-target data.

IV. THE USE OF INTERVENTION ANALYSIS TO CHARACTERIZE TARGETS[2]

In the previous section, an ARIMA model was used to characterize the non-target data. An additional requirement is to model the data when a target is present. The approach used is referred to as intervention analysis. By intervention we mean that a target intervenes or projects itself on the non-target data causing changes to the time series.

In Figure 3 a typical plot of the MMW sensor's responses to a target is shown. This target response is denoted by the negative dip in the stationary time series at approximately t = 275. In this section, a dynamic intervention model is being proposed to describe the targets' responses. This dynamic model is illustrated in Figure 11. For the present, the target will be denoted by a pulse indicator function.

$$P_t(T) = \begin{cases} 1, & \text{Targets} \\ 0, & \text{Otherwise} \end{cases} \tag{7}$$

where T is the number of pulses in the signal. That is, when the sensor detects the occurrence or nonoccurrence of a target the variable takes on the value 1 or 0. The input variable is denoted by $\xi_t = W_o P_t(T)$. This dynamic model takes the form, $Z_t = Y_t + N_t$, where the Y_t represents the additional effect of an intervention over the stochastic noise (N_t).

In the attempt to model targets, an intervention dynamic model of the following form is proposed:

$$Z_t = \frac{(1 - W_1 B)}{(1 - \delta_1 B)} W_o P_t(T) + \frac{(1 - \theta_1 B)}{(1 - \phi_1 B)} a_t \tag{8}$$

Where $P_t(T) = \begin{cases} 1, & \text{Targets} \\ 0, & \text{Otherwise} \end{cases}$ and $a_t = N(0, \sigma_a^2)$.

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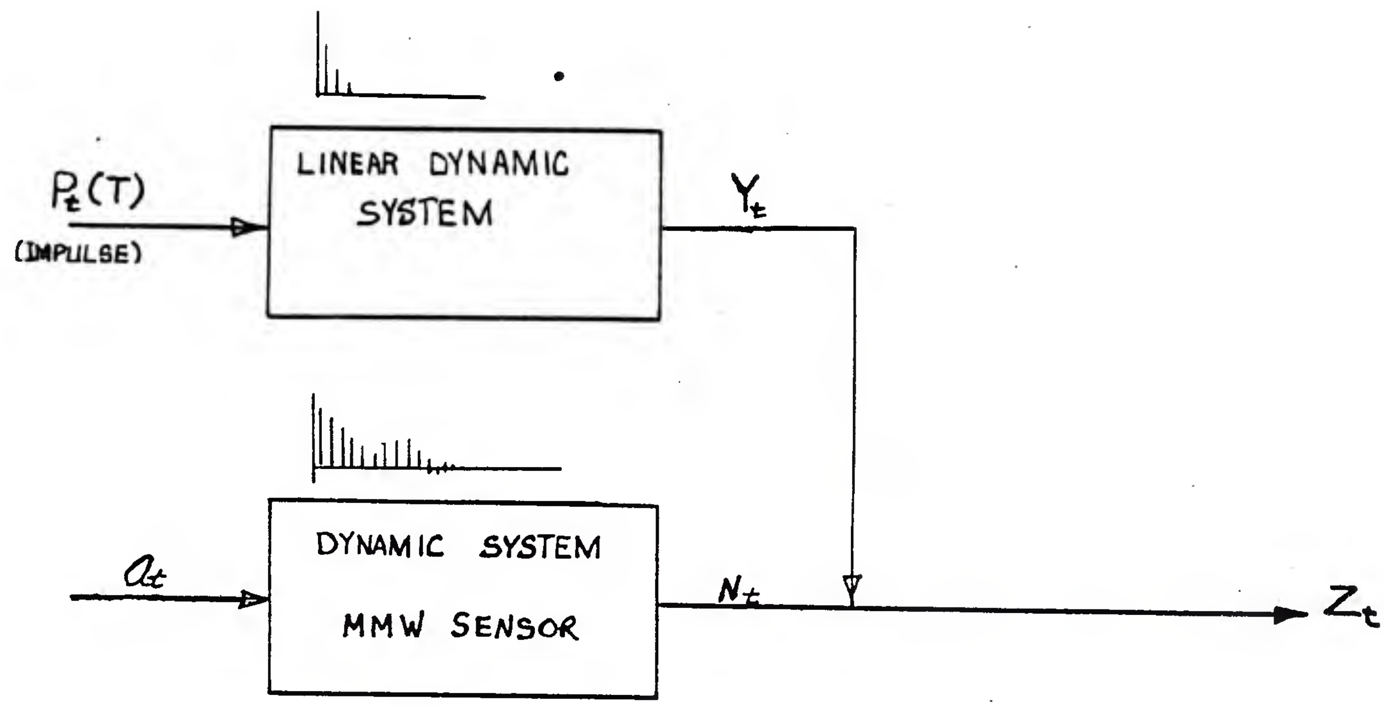
[2] Box, G. E. P. and Tiao, G. C., "Intervention Analysis with Applications to Economic and Environmental Problems," Journal of the American Statistical Association, Vol. 70, No. 349, March 1975.



$$Z_t = Y_t + N_t$$

Figure 11. Intervention Model for a Dynamic System with Superimposed ARIMA Model

This structure is being proposed because:

(1) In Sections II and III the noise is modeled by $(1 - \phi_1 B)N_t = (1 - \theta_1 B)a_t$ and the estimated parameters are approximately

$$\hat{\phi} \approx .80$$

$$\hat{\Theta} \approx -.62$$

$$\hat{\mu}_a \approx 0.00$$

$$\hat{\sigma}_a \approx 1.78$$

(2) We take the approach that the raw signals of both background noise and target will filter through the identical MMW sensor. Hence, both signals are likely to have similar dynamic structure. The above information resulted in the following time series intervention model where the previous estimated parameters are substituted into Equation (8).

$$Z_t = \frac{(1 + 0.62B)}{(1 - 0.8B)} W_o P_t(T) + \bar{\mu} + \frac{(1 + 0.62B)}{(1 - 0.8B)} a_t \tag{9}$$

where $P_t(T) = \begin{cases} 1, & \text{Target} \\ 0, & \text{otherwise} \end{cases}$

$$W_o < 0.$$

Before continuing, a look at the dynamic response to a pulse input under the proposed intervention structure would be helpful. (See Table 8.)

Let
$$Y_t = \frac{(1 - W_1 B)}{(1 - \delta_1 B)} W_o P_t(T) \tag{10}$$

or
$$Y_t = \delta_1 Y_{t-1} + W_o P_t(T) - W_1 W_o P_{t-1}(T) \tag{11}$$

The initial responses will be a step of size W_o, followed by (T-1) additional increasing steps. This dynamic intervention model would be at its maximum value at the Tth step (the pulse length) and would start to decay at a rate δ_1. If W_o were negative ($W_o < 0$) the response of the pulse input would also be negative similar to the actual targets' responses. That is, the response would occur in the negative direction instead of the positive direction as shown in Table 8. The number of pulses needed to generate these dynamic responses can almost be interpreted as the number of times the MMW sensor detects the presence of the intervention (target). The size of the adjacent response can be thought of as a function of W_o, the intensity of the given target. That is, if the adjacent step responses are large, the target temperature characteristics are high. Hence, there exists good rationale for the parameters W_o and the dynamic intervention model, which are summarized below:

TABLE 8. THE DYNAMIC RESPONSES OF A PULSE INPUT FOR THE PROPOSED INTERVENTION STRUCTURE.

$$Y_t = \delta_1 Y_{t-1} + W_0 \; P_t(T) - W_1 W_0 \; P_{t-1}(T)$$

where δ_1 = 0.8
W_0 = 1.0
W_1 = -0.62

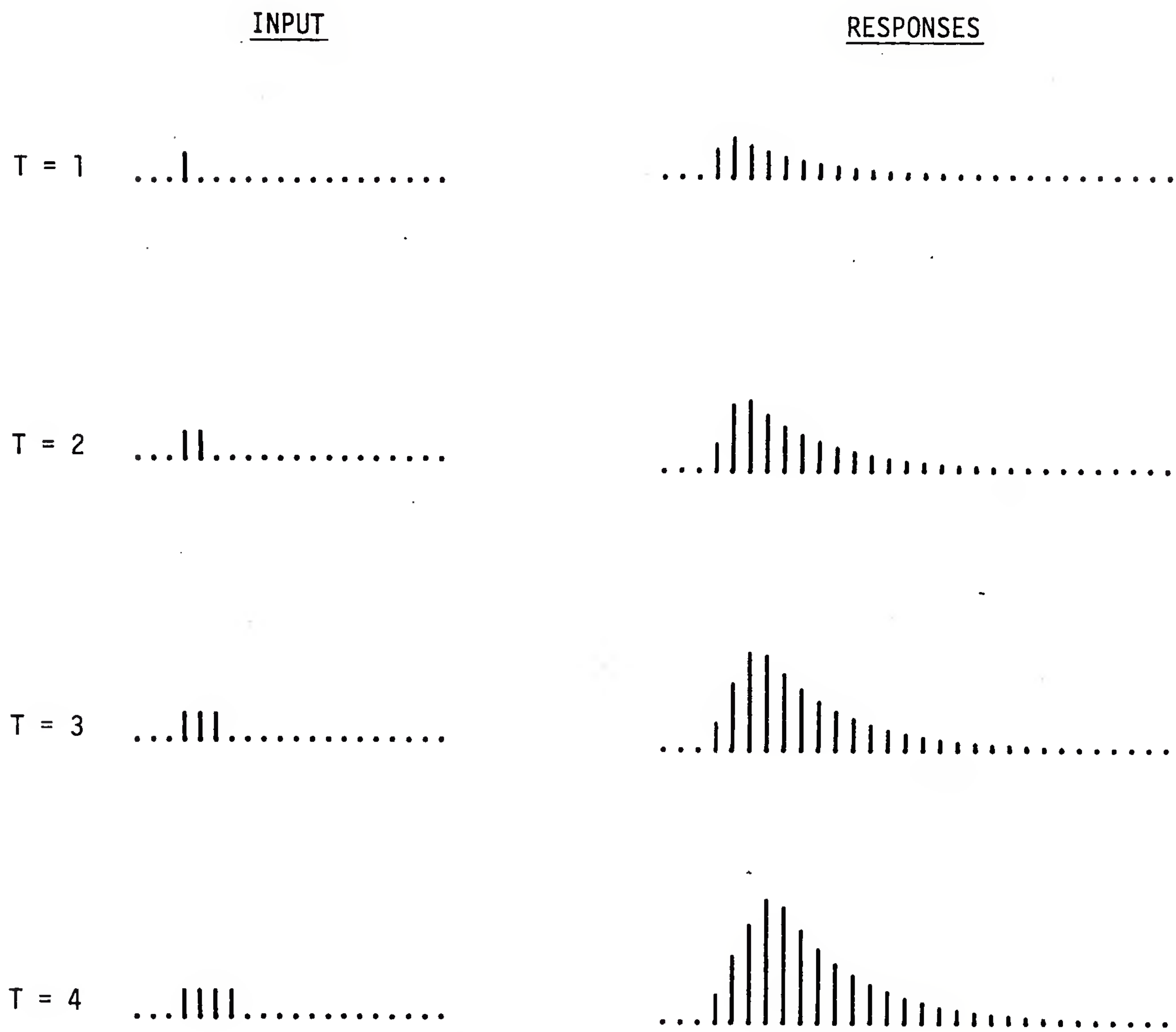
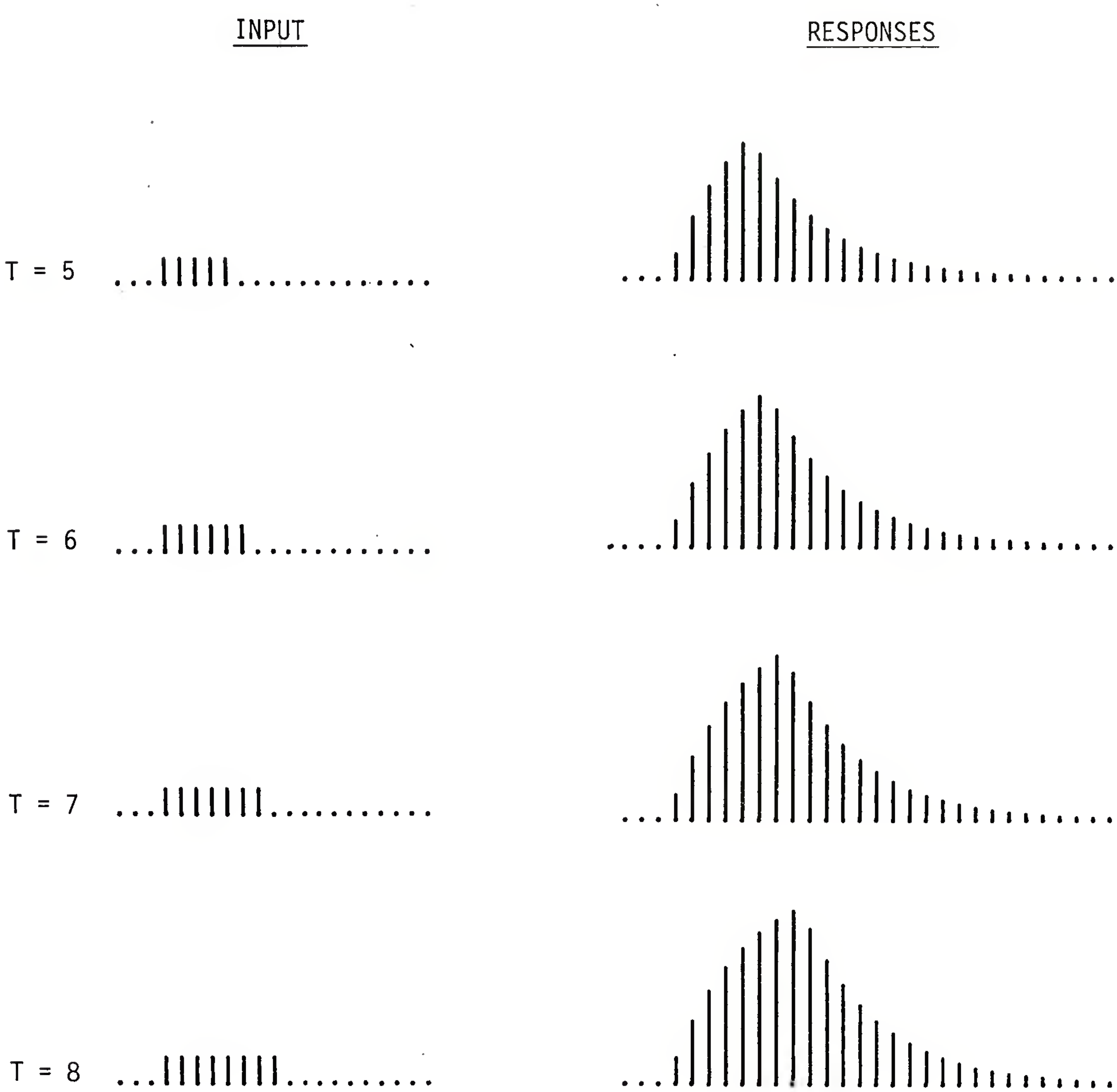


TABLE 8. (Continued) THE DYNAMIC RESPONSES OF A PULSE INPUT FOR THE PROPOSED INTERVENTION STRUCTURE.



(i) The presence of a target is indicated by a pulse (intervention) of length equal to that of a target signal.

(ii) The raw target signal, like the background noise, should behave in a similar dynamic structure (same ARIMA model) $(1 - \delta_1 B)Z_t = (1 - W_1 B)\xi_t)$.

(iii) The number of pulse inputs is an indication of how long the target is being sensed by the MMW sensor.

(iv) The step "W_o" is an indication of the contrast temperature $T(°K)$ which is a characteristic of the target (intervention).

This representation is in its formative stage and improvements are planned as more target data become available. It is believed that $\xi_t = W_o P_t(T)$ is not in reality a constant, but a function of the size and temperature characteristics of the intervention (target).

This intervention model was used to simulate a number of time series that are plotted in Figures 12 through 17. These plots were generated with pulse inputs of length $T = \{15, 20, 25\}$ and $W_o = -1.0$. The reason for two plots for each case ($T = 15,20,25$) was to demonstrate that each simulated intervention will result in slightly different signals, with basic similarities.

These results are very similar to Figure 3 and Figure 18, actual MMW data. A closer look at Figures 18 and 19 indicates an intervention duration of approximately $T \approx 25$. A comparison of the actual target data (Figure 18) and the simulated data ($T = 25$) (Figure 16) shows remarkable agreement. Figure 20 is another simulated intervention of this dynamic model (9) with a pulse of length $T = 25$.

V. SUMMARY

The MMW non-target data of August 1978 was analyzed by the Box and Jenkins time series approach. This analysis resulted in an ARIMA (1,0,1) model with consistent estimated parameters for both ϕ_1 and θ_1 as well as $a_t = N(0,\sigma_a^2)$ (white noise). The ARIMA (1,0,1) model characterizes the data remarkably well.

The MMW target data was modeled using a dynamic intervention approach. The dynamic model proposed is promising in that targets can be characterized as interventions with background noise.

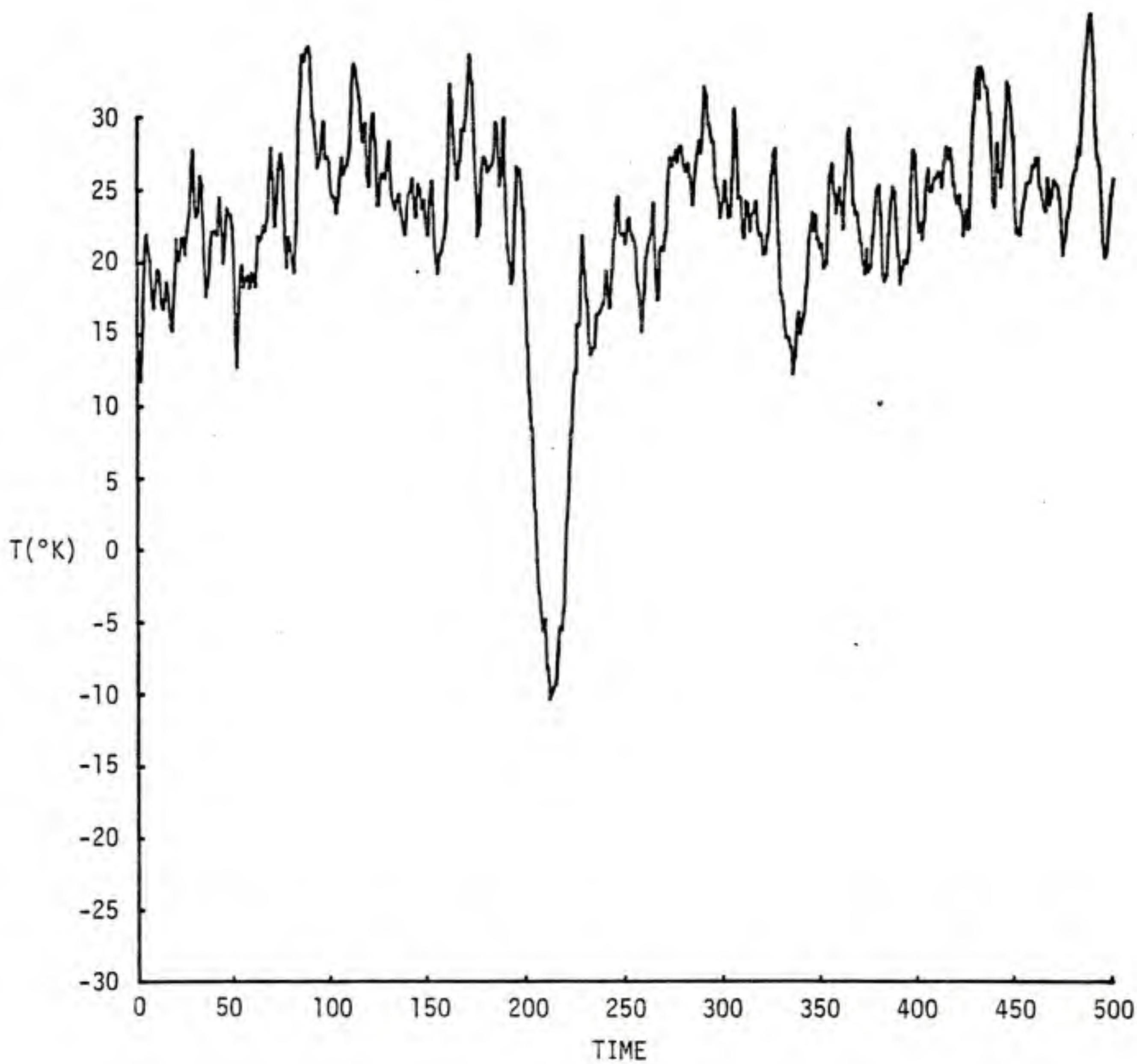


Figure 12. Simulated Target P_t (15)

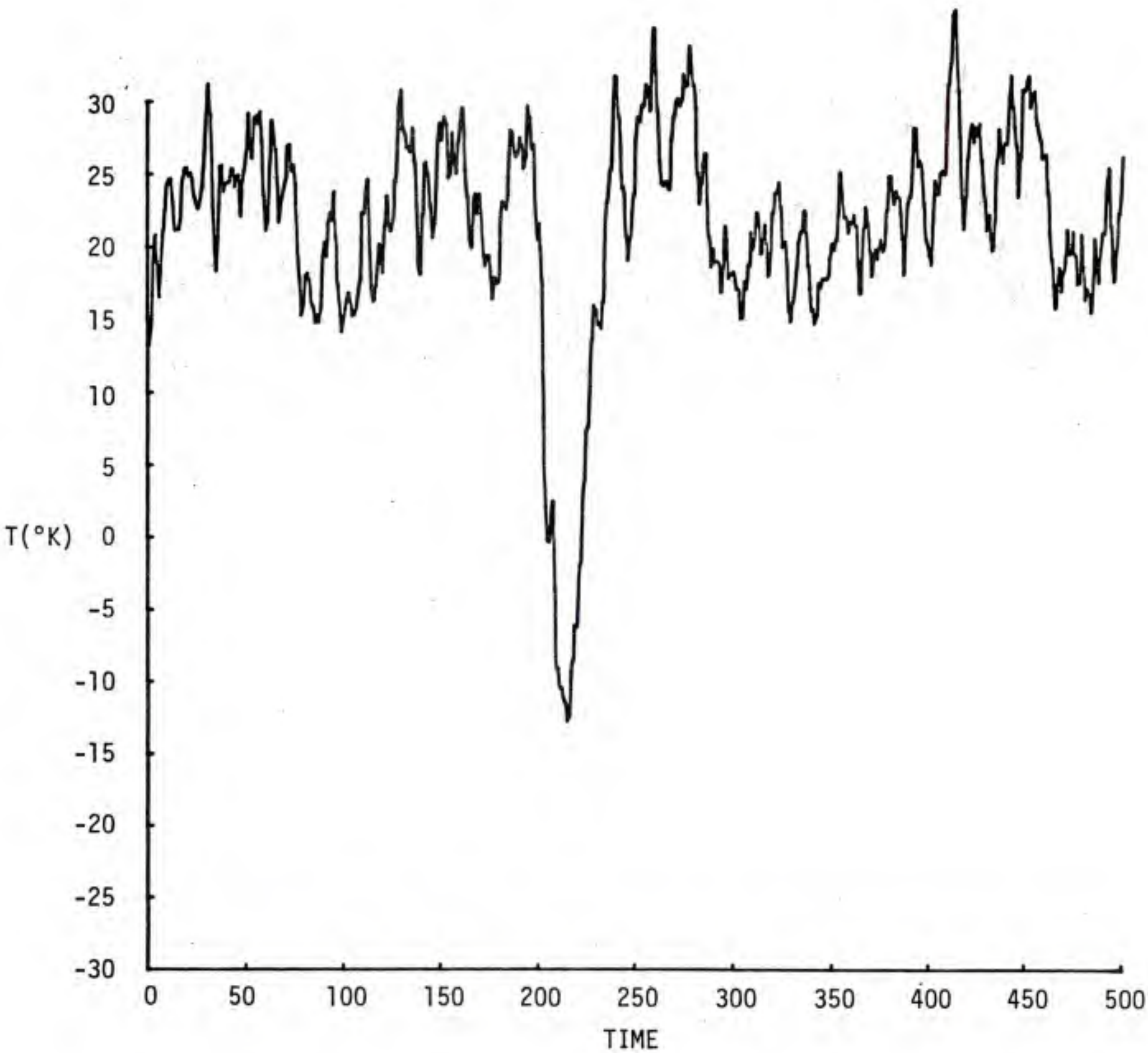


Figure 13. Simulated Target P_t (15)

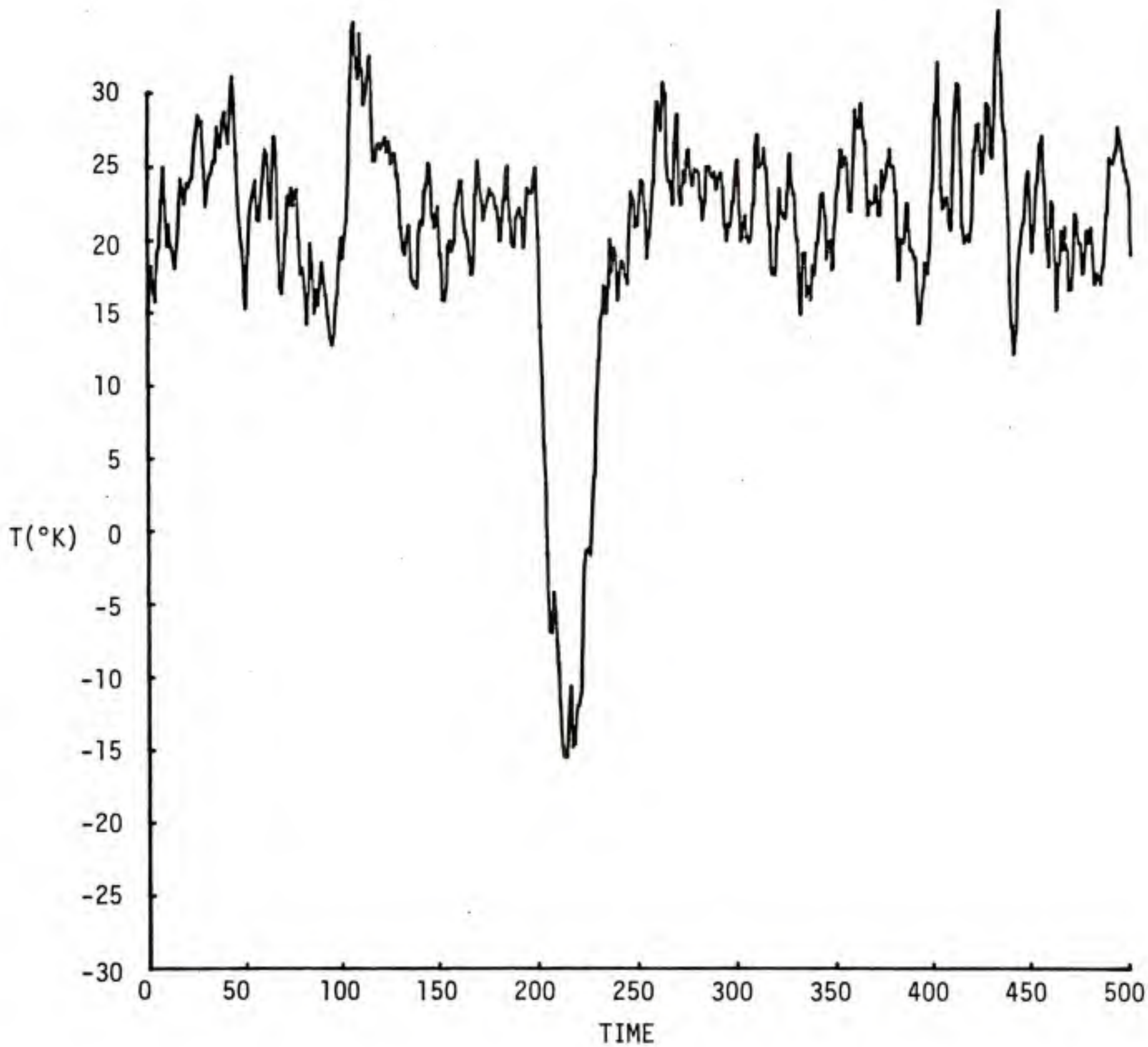


Figure 14. Simulated Target P_t (20)

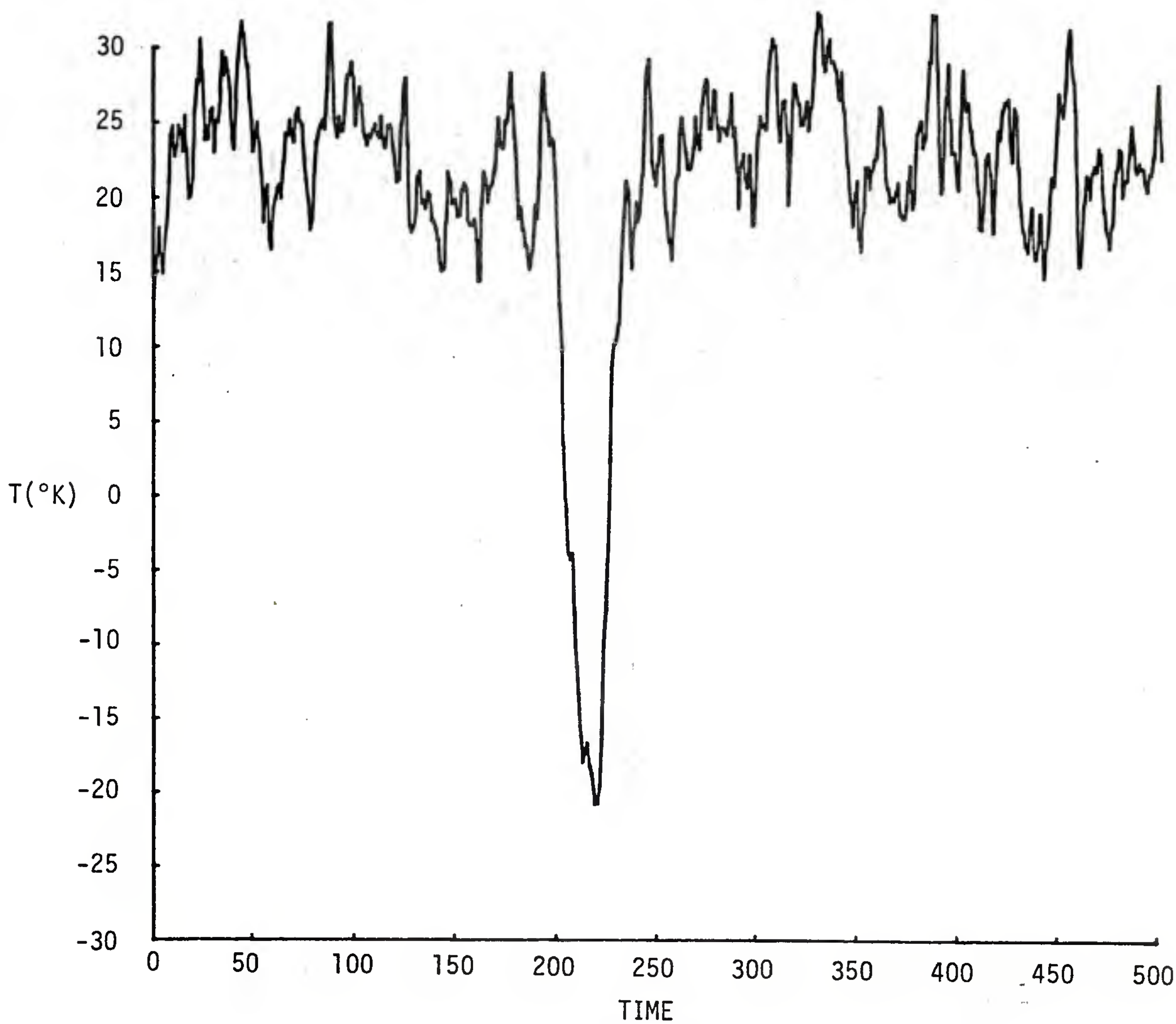


Figure 15. Simulated Target P_t (20)

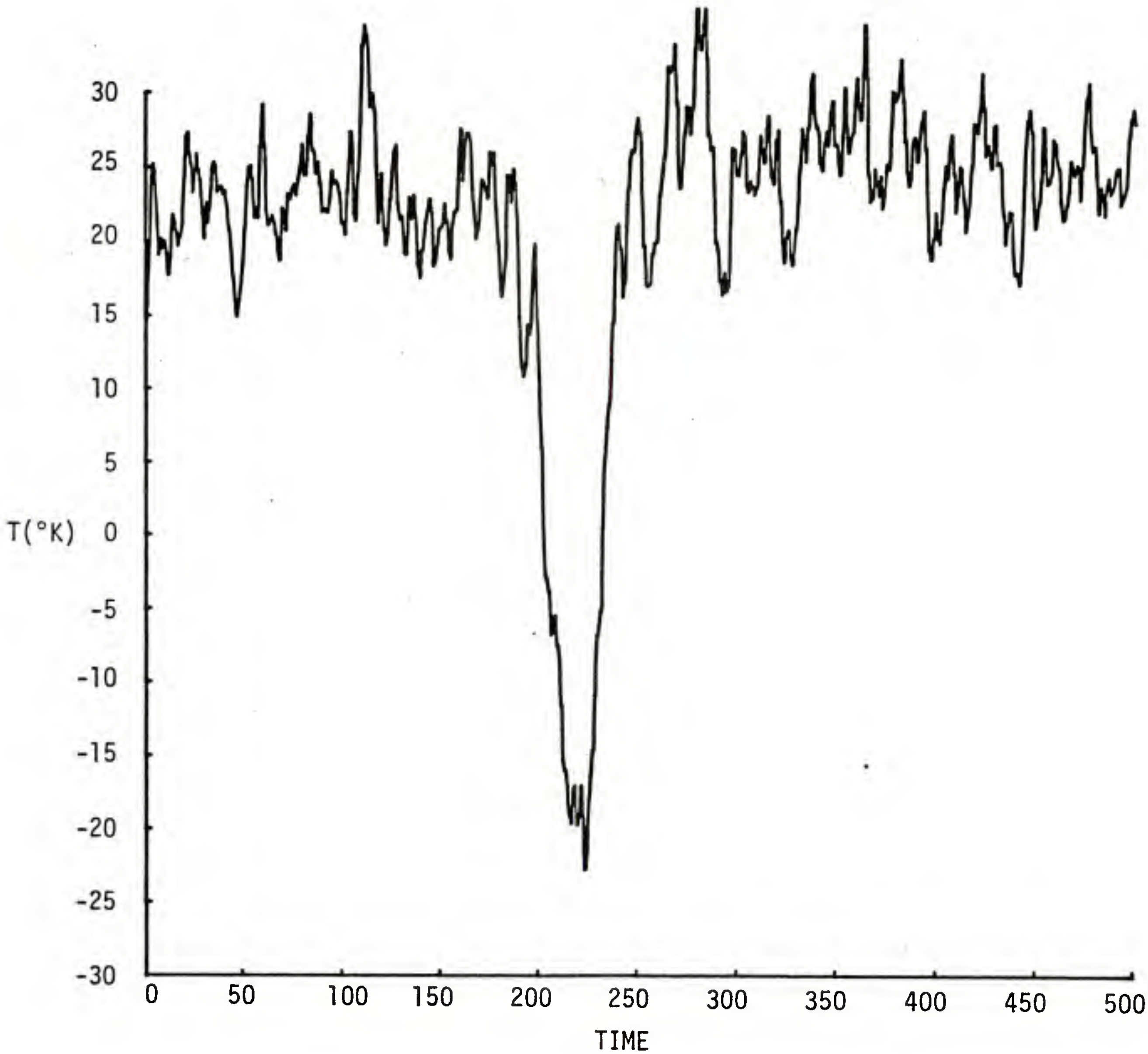


Figure 16. Simulated Target $P_t(25)$

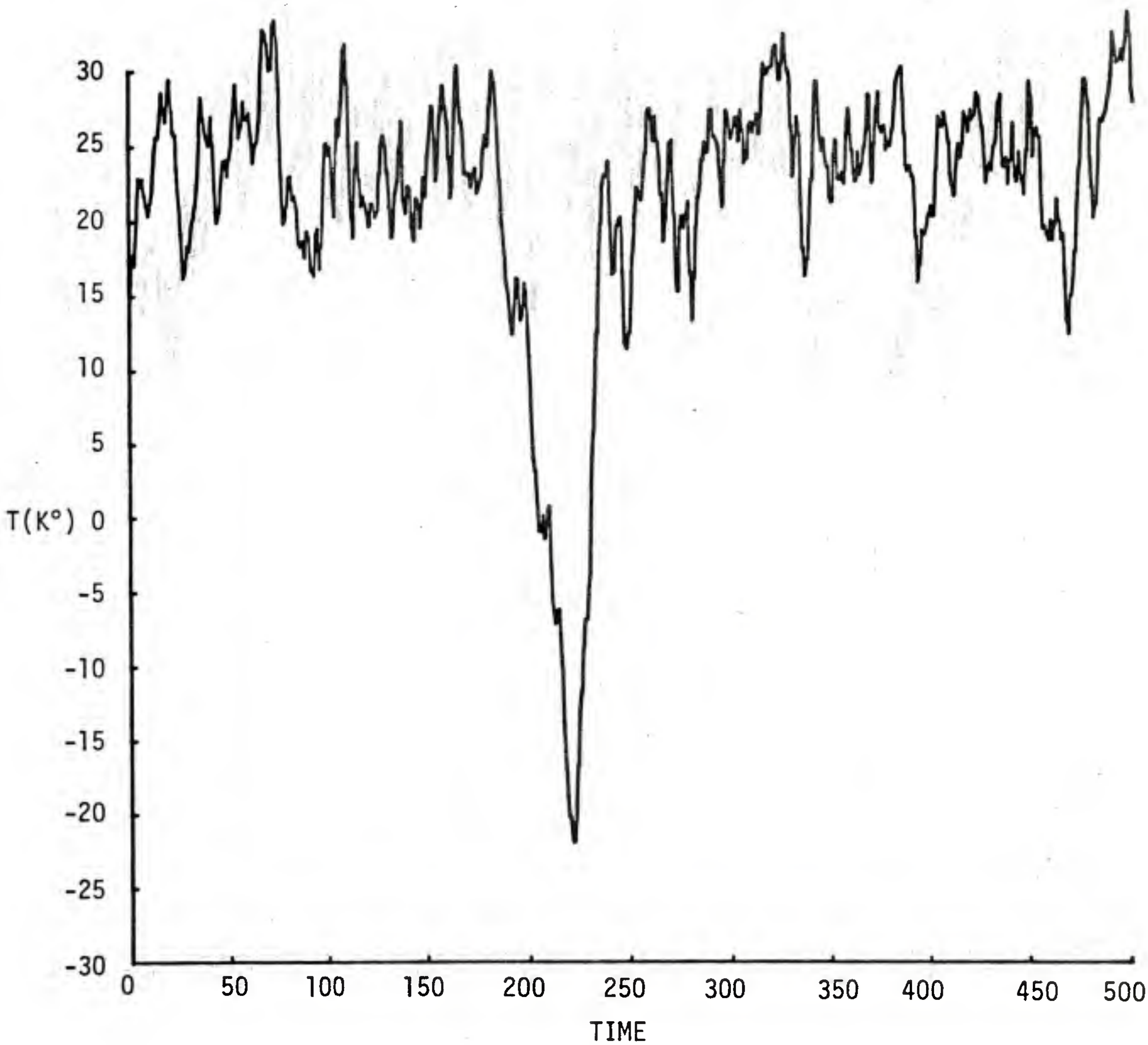


Figure 17. Simulated Target $P_t(25)$

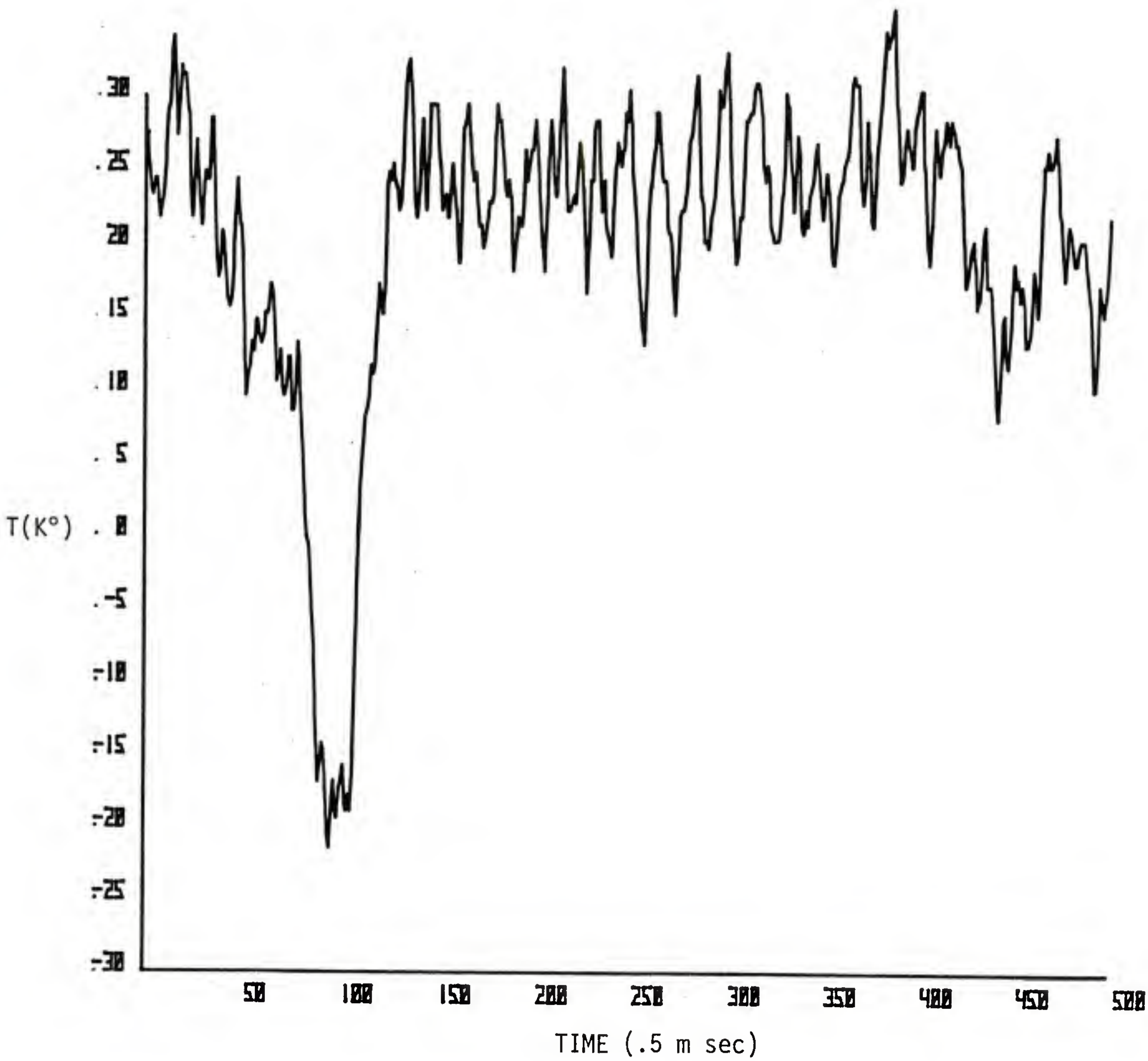


Figure 18. Actual MMW Target at 30 Meters.

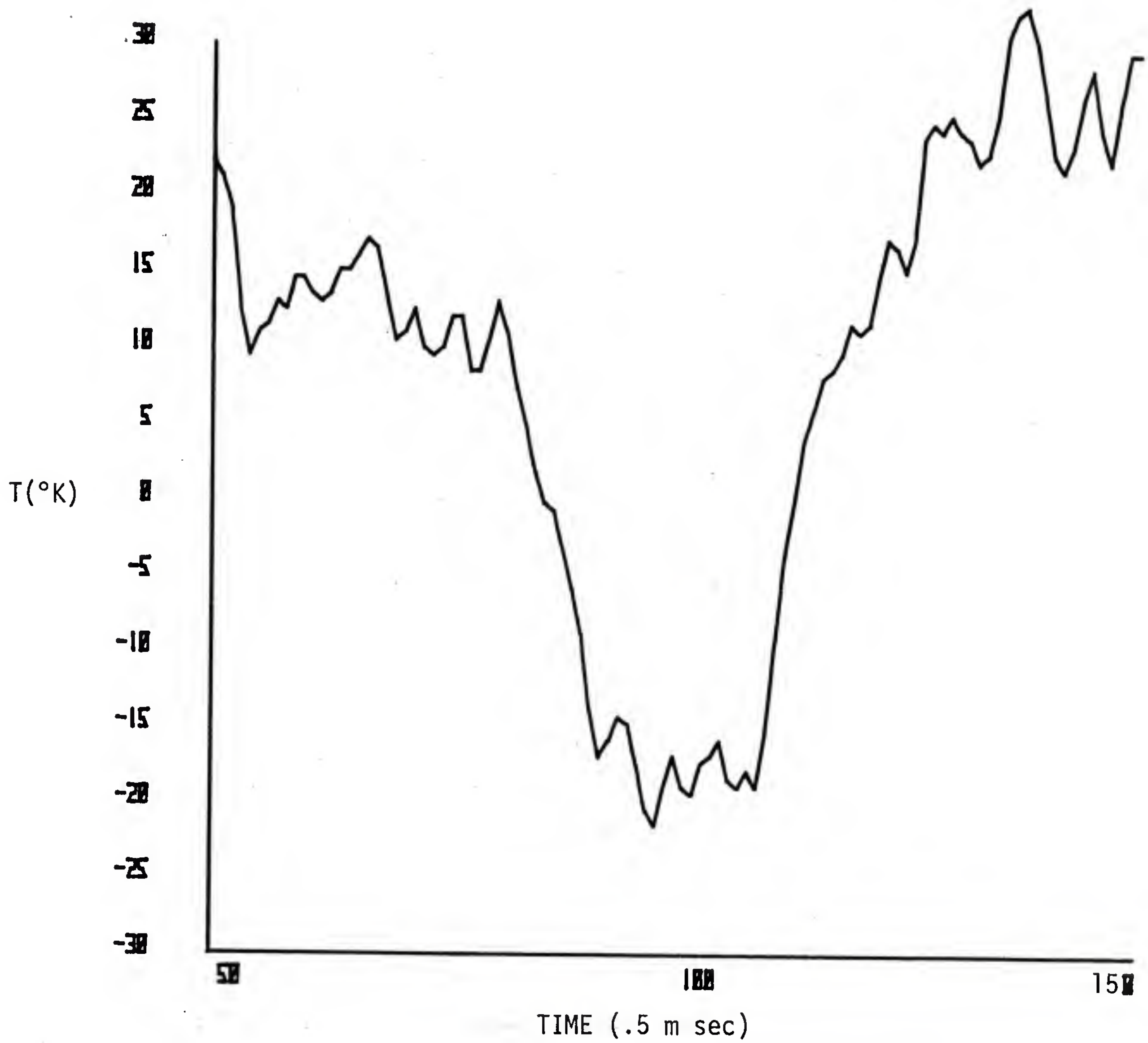


Figure 19. A closer Inspection of Figure 18. Actual MMW Target at 30 Meters.

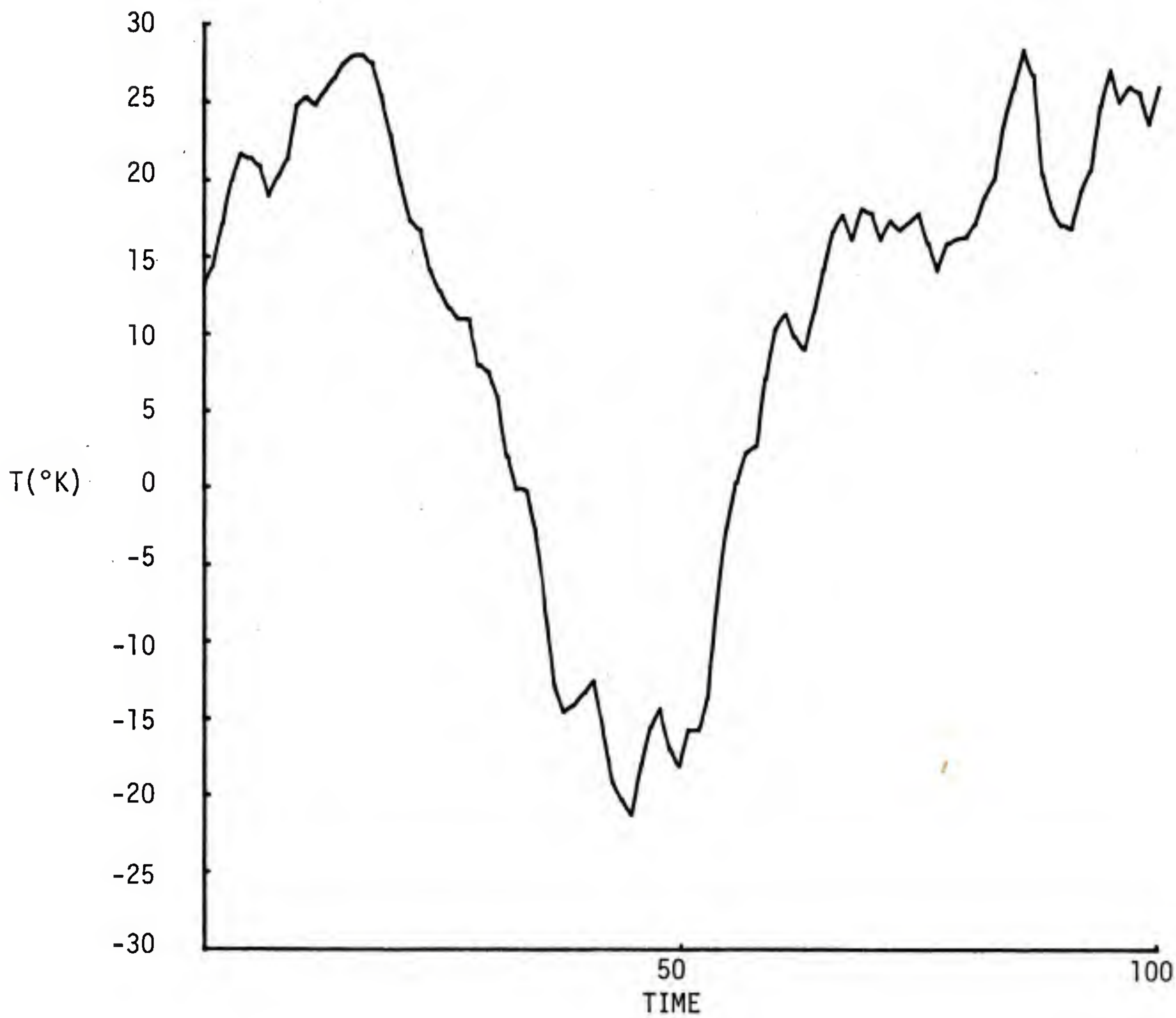


Figure 20. A Simulated Intervention of T = 25.

REFERENCES

1. Box, G.E.P. and Jenkins, G.M., Time Series Analysis: Forecasting and Control, San Francisco, CA, Holden-Day, 1970.

2. Box, G.E.P. and Tiao, G.C., "Intervention Analysis with Applications to Economic and Environmental Problems," Journal of the American Statistical Association, Vol. 70, No. 349, March 1975.

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